Management Science

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http://pubsonline.informs.org/journal/mnsc

MANAGEMENT SCIENCE
Articles in Advance, pp. 1–17
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

Signaling Status: The Impact of Relative Income on Household Consumption and Financial Decisions

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Received: June 6, 2018
Revised: April 22, 2019; August 23, 2019
Accepted: December 1, 2019
Published Online in Articles in Advance: May 29, 2020

https://doi.org/10.1287/mnsc.2019.3577

Abstract. This paper investigates the importance of status in household consumption and credit decisions using data from the Survey of Consumer Finances linked to tract-level data in the American Community Survey. We find that relatively richer households in the census tract use more debt and spend more on high-status cars. Also, county-level evidence shows that the consumption of high-status cars is higher in more unequal counties. These results suggest that greater income heterogeneity might shape household consumption and credit decisions, as relatively richer households signal their higher status to their neighbors through the consumption of visible status goods.

History: Accepted by Tomasz Piskorski, finance.
Supplemental Material: The online appendix is available at https://doi.org/10.1287/mnsc.2019.3577.

Keywords: consumption • inequality • debt

1. Introduction

The sharp rise in income heterogeneity in the United States and the ongoing debate over the political and economic effects of income inequality have sparked growing interest in understanding how status and relative income differences might affect consumption and credit decisions.[1] Arguments that emphasize conspicuous consumption note that higher income individuals might use visible status goods, such as luxury cars and public charitable donations, to signal their higher income rank or social status in order to gain access to lucrative social networks (Bagwell and Bernheim 1996, Glazer and Konrad 1996).[2] In an influential paper, for example, Charles et al. (2009) find evidence that the conspicuous consumption motive might explain most of the differences in visible consumption goods across racial groups in the United States.

A related idea centers on "keeping up with the Joneses," whereby the less affluent might accumulate unsustainable debt levels in order to match the visible consumption of their more well-to-do neighbors. There is also compelling microeconomic evidence suggesting that this type of aspirational behavior might influence credit and consumption decisions. Agarwal et al. (2020), for example, document that lottery winnings can increase borrowings and bankruptcies among less fortunate nearby neighbors.[3] Similarly, Georgarakos et al. (2014) find that the likelihood of financial distress increases among those who perceive themselves to be poorer than their peers.[4] More aggregate evidence in Bertrand and Morse (2016) also suggests that keeping up with the Joneses can lead to financial duress among the less well-to-do.

This paper provides new evidence on how household income rank at the very local level might shape a comprehensive set of credit and consumption decisions. This paper uses data from households in the Survey of Consumer Finances (SCF), including the panel, that identify the household's census tract, along with other key variables heretofore unavailable. This allows us to link each household to census tract income and demographic data from the American Community Survey (ACS). A census tract consists of about 4,000 people and most likely comprises a household's immediate neighbors. These data can both help address a number of important identification challenges and afford relatively direct tests of the effects of income rank on a broad spectrum of consumption and credit decisions.

In particular, one key challenge to credible inference stems from identifying a household's reference group. Many of the studies on peer effects in the United States, such as Charles et al. (2009) and Bertrand and Morse (2016), use aggregate state-level data to identify a household's reference group. But the choice of reference group is often linked to an individual's sense of self or identity and is multifaceted and context dependent, making state-level variables a potentially noisy proxy for a household's reference group (Akerlof and Kranton 2000).

For example, within a large state such as California—a state with 40 million people—an individual might more readily identify herself by the college she attended and donate to her alma mater in order to signal her position in that specific income distribution and impress her former classmates. The same individual might also donate to the neighborhood library and consume visible status goods to signal her income rank to her nearby neighbors—the people with whom she has the most social interactions. The income distribution of California—made up of mostly anonymous strangers with whom the individual rarely interacts—might have little impact on her consumption decisions.

Measuring permanent income also presents another challenge to identification. Standard economic theory predicts that permanent income likely plays an important role in household financial decisions. However, both permanent income and past consumption habits, as well as a household's uncertainty surrounding its future income, can be difficult to observe in the available U.S. micro data sets that also record detailed consumption expenditures. Omitting these variables can make it difficult to interpret causally tests of signaling behavior in consumption (Carroll 1997).

The relatively fine geographic information available in a linked version of the SCF can address some of these challenges. Neighborhoods are a key source of identity for many households, and there is substantial evidence that the social contacts formed from the interactions among neighbors can shape a wide range of outcomes, making geographically close neighbors a prime reference group for many kinds of signaling behavior.[5] In addition, the SCF provides relatively detailed data on permanent income, a household's income expectations, and experience with credit availability, allowing us to include reasonably informative proxies for these concepts when constructing these household-level tests.

A related concern is that selection into a census tract is nonrandom, and endogenous sorting can bias these results even when using the rich set of available controls. Households, for example, that have an intrinsic taste for visible luxury goods might also prefer to live in less expensive tracts so that they can better indulge in these goods. To help address biases that might arise from endogenous preferences, we use the 2007–2009 SCF panel to absorb unobservable household-level characteristics, such as time-invariant consumption preferences.

We find that households use visible status goods to signal their relative income rank. By definition, visible status goods are expensive, and we also find evidence that the conspicuous consumption of these goods affects credit usage. A 1–standard-deviation increase in a household's income rank—computed relative to its census tract neighbors—is associated with a 0.38-standard-deviation increase in the log of credit card balances.[6] Evaluated at the mean credit card balance in the sample, this increase in rank suggests a $3,254 increase in credit card balances. A similar increase in rank is also associated with about a $300 increase in debt service payments and about a 1.5-percentage-point increase in the probability of bankruptcy. These results are robust to a large number of controls, including nonparametric models of income. They also persist across the 2000s and are present, but smaller, when using household fixed effects in the 2007–2009 panel.

Cars are the canonical status good, and we also find evidence that income rank has a large significant effect on car consumption along a number of dimensions. A 1-standard-deviation increase in income rank is associated with a 17% increase in the value of a household's most expensive car. A similar increase in rank is also associated with a 3.4-percentage-point rise in the probability of owning a status car, such as a BMW or Mercedes-Benz; a 16.4% rise in the average value of all cars; and a 15.2% drop in the age of the household's youngest car.

This household-level evidence suggests that the demand for high-status cars should be higher in areas with a greater dispersion in incomes. By contrast, in areas where incomes are known to be more homogeneous, communicating information about status is likely to be less important in the decision to buy a car, reducing the demand for high-status cars. We use a new proprietary county-level data set from Polk on every new car sold in the United States to investigate further the aggregate consequences of signaling. We find a large positive association between income inequality inside a county and the fraction of high-status cars sold. And consistent with the household-level results, we find higher levels of consumer leverage in more unequal counties.

Taken together, these results suggest that signaling to geographically proximate neighbors might play an important role in a household's consumption and credit decisions and is supportive of theories that emphasize status motives in consumption (Glazer and Konrad 1996). These findings can also help us interpret the simultaneous rise in inequality along with the increase in consumer indebtedness and the growing consumption of status goods over the last few decades across the world. The rest of this paper is structured as follows. In Section 2, we make precise the main hypothesis and describe the various data sources. Section 3 focuses on the household-level results, whereas Section 4 considers the county-level evidence. Section 5 concludes.

2. Hypothesis Development and Data

2.1. Hypothesis Development

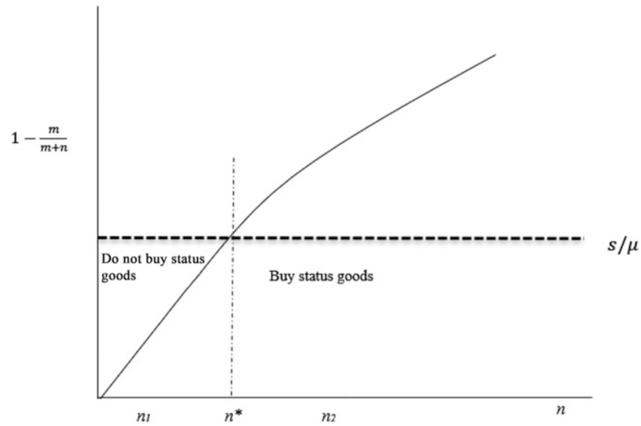
This subsection makes concrete the hypothesis that an individual's relative income rank might determine her spending on costly visible consumption goods. To this end, we use a simplified version of the model in Glazer and Konrad (1996). A central prediction in Glazer and Konrad (1996) is that individuals give to charities or consume visible status goods to signal their relative wealth. This demonstration of high relative wealth, in turn, allows donors to socialize with others from the same or higher social status, giving them access to lucrative contacts. Property 4 of the model predicts that exogenously adding poorer people to the population, such that the relative income rank of the original donors increases, causes these original donors to make higher donations or buy visible status goods in order to signal their relative income rank.

To see this basic prediction from Glazer and Konrad (1996), suppose that there are just two types of individuals: high income ($\bar{y}$) and low income ($\underline{y}$). There are m high-income individuals and n low-income people, so that the unconditional probability that individual i is high income is $P(y_i = \bar{y}) = \frac{m}{m+n}$. There are also two types of goods: a private good, c, and a visible status good, such as a luxury car, that can be purchased for a price s. Buying the status good increases beliefs by others that the individual is of "high rank" or "rich." That is, the conditional probability that an individual is high income is $P(y_i = \bar{y}|s) > \frac{m}{m+n}$.

As in Glazer and Konrad (1996), being seen as rich improves utility. In a simple linear representation of this idea, expected utility conditional on purchasing the status good is $u_s = y_i - s + \mu P(y_i = \bar{y}|s)$, where μ is the value of being perceived as rich by others—the value of access to exclusive social networks, for example. Expected utility conditional on not investing in the visible status good is $u = y_i + \mu \frac{m}{m+n}$. A separating equilibrium exists so that high-income individuals buy the status good if $P(y_i = \bar{y}|s) - \frac{m}{m+n} > \frac{s}{\mu}$. In this setting, the prediction from Glazer and Konrad (1996) that an increase in the number of poor people leads to increased signaling behavior on the part of the original rich occurs if $\frac{\partial P(y_i = \bar{y}|s)}{\partial n} > -\frac{m}{(m+n)^2}$.

Intuitively, adding poor people to the neighborhood reduces prior beliefs that any individual is rich. If, however, beliefs that an individual is rich conditional on observing the status good does not decline as quickly when the poor increases, then the incumbent rich now has a greater incentive to buy the visible status good. Figure 1 sketches this idea for the extreme case when the status good is perfectly revelatory: $P(y_i = \bar{y}|s) = 1$ —say, a late model Mercedes-Benz S class sedan. If the number of poor in the population is so small as to be to the left of n^*, such as at point n_1, then the rich has no incentive to buy the sedan. But an influx of poor into the neighborhood that increases the number of poor to a point such as n_2 will induce the original rich to buy the Mercedes-Benz.

Figure 1. The Decision to Buy Status Goods and the Number of Poor People



Note. This figure shows that when the number of poor people exceeds n^*, it is optimal for the rich to buy status goods.

This example is highly stylized. Notably, Glazer and Konrad (1996) allow for a continuum of types, use a standard separable, concave utility function, and a monotonic function mapping donations to beliefs about income. The richness of that setup allows for greater nuance in the effects of a mean preserving spread in the income distribution on signaling behavior. For instance, if donations are a convex function of income, then redistribution that reduces inequality also reduces donations. Our stylized example does make concrete, however, the hypothesis that an increase in an individual's income rank—or equivalently, a decline in average income in the area—can generate increased purchases of visible status goods. Because status goods are almost by definition expensive, with most households relying on bank and revolving consumer credit to purchase new cars, luxury clothes, and other goods, signaling through visible status goods is also likely to engender an increase in consumer indebtedness.

To test the effect of income rank on credit decisions and the consumption of status goods, we turn to household data from the SCF linked to neighborhood data in the ACS. This approach combines high-quality survey data on credit, consumption, and other household observables with detailed income distribution data at the census tract or "neighborhood" level. Neighbors are both an important reference group for most households and an important source of contacts and social networks. The data are thus well suited to testing the hypothesis that signaling behavior might influence credit and consumption decisions.

In particular, consider a cross section of households. Let c_i denote the consumption of status goods by household i, such as the value of a high-status automobile or the household's indebtedness. Let r_i measure household's i relative income rank in the neighborhood—the census tract in the baseline specification. The household's permanent income, y_i, as well as demographic variables, X_i, is also expected to shape the consumption decision, and the estimating equation is

$$c_i = \alpha_0 + \alpha_1 r_i + \alpha_2 y_i + \boldsymbol{X}_i \boldsymbol{\beta} + e_i. \tag{1}$$

The signaling hypothesis in Glazer and Konrad (1996) predicts that $\alpha_1 > 0$: an increase in income rank—say, because of an influx of poorer households—that moves an individual from the median to the 90th percentile in the income distribution will cause the individual to spend more on visible consumption goods.

Unfortunately, households do not randomly locate into census tracts, and measurement and identification challenges make it difficult to causally interpret estimates of α_1 in Equation (1). Notably, because the choice of reference group or neighborhood can be endogenous, it is difficult to determine whether estimates of $\alpha_1$reflect status considerations or unobserved factors that determine both a household's status relative to its selected reference group and the household's consumption behavior (Lowenstein et al. 2003).

For example, because social contacts with nearby neighbors can shape a wide range of household outcomes, households might select into a neighborhood based on characteristics that could also be correlated with their income rank inside the tract (Kuminoff et al. 2013). Higher income households with a preference for expensive, ostentatious consumer goods might also select into lower-income neighborhoods with more affordable housing, allowing them to indulge better in their preference for luxury goods. In this case, positive estimates of $\alpha_1$would likely reflect unobserved consumption preferences rather than status behavior.

Similarly, households with a preference for better public goods such as education or other local amenities or those who believe that their future earnings will rise rapidly might sort into neighborhoods with more expensive housing costs and richer neighbors, leaving these households with both a lower income rank and less disposable income to purchase status goods. The neighborhood itself could be a status symbol, and some poorer households may trade off the prestige of the address for less consumption. Apart from selection, defining the neighborhood or reference group can also make it difficult to interpret α_1. Although some individuals might view the state or metropolitan statistical area population as their reference group, most will likely regard their immediate neighbors as a relatively more important source of valuable social contacts and a key reference group.

To help address these measurement and identification concerns, we make use of the internal SCF waves throughout the 2000s, which identify the household's census tract. When linked with the ACS, we can identify the household's income rank relative to its census tract neighbors for each household in our sample. Income rank is defined as the household's income percentile relative to the income distribution inside the tract. This level of detail provides a powerful and unique opportunity measure the effects of status on consumption decisions.

The SCF also provides a rich set of demographic and economic variables that can be used to address partially the problem of unobserved preferences and endogenous selection. Some of these variables include the length of time that a household has lived inside the census tract, as well as various measures of local housing costs, including costs specific to each household.

However, despite controlling for a rich set of observables, the problem of endogenous selection can still engender alternative interpretations of α_1. We thus make use of the 2007–2009 SCF panel. To the extent that household preferences remained fixed over this period, then if after the inclusion of household fixed effects α_1 remains positive, we can surmise that time-invariant household preferences are unlikely to be driving these results.

The panel also helps us to judge the possible influence of migration over the 2007–2009 financial crisis on our results. That is, negative unobserved shocks during this period could induce relatively richer households to move to census tracts where these migrants rank lower in the income distribution. These negative shocks could also affect the consumption of the migrants, biasing inference. However, the data show that between 2007 and 2009, those that moved census tracts were at the 47th percentile of the income rank in their original tract and at the 48th percentile in their new tract, suggesting that downward mobility across tracts might not be a significant source of bias (Bricker and Bucks 2016).

Beyond the problems of endogenous selection and the appropriate geographic definition of neighborhood, the empirical analysis must also address the fact that standard economic models generally relate consumption decisions to a household's expectation of permanent income. Reliable measures of permanent income are not often available in microeconomic data sets, and estimates of $\alpha_1$are likely to be biased without accurate measures of permanent income. Fortunately, the SCF includes a number of questions that plausibly measure both permanent income and overall income expectations, and in the next section we describe these and other data in greater detail. Also, durable goods consumption often depends on credit access, and the SCF also allows us to measure a household's access to credit. We describe these data next.

2.2. Data

We use data from three main sources to evaluate the importance of status in the consumption decision: (1) the SCF, a household-level data set produced every three years by the Federal Reserve Board;[7] (2) the Polk proprietary data that provide, by county of purchase, the make and model of every new car sold in the United States since 2002; and (3) the ACS, a well-known public data source produced by the U.S. Census Bureau that provides census tract demographic information. We next describe our use of the data sets.

2.2.1. The Survey of Consumer Finances. The SCF is normally conducted by the Federal Reserve Board (FRB) as a triennial cross-sectional survey.[8] This paper draws on data from the 2004, 2007, and 2010 SCF cross sections, encapsulating the boom as well as the crisis and steep subsequent worsening of U.S. households' balance sheets. We also use data from the special 2007–2009 SCF panel, which collected follow-up information about the 2009 circumstances of the 2007 SCF respondents.

The SCF is generally viewed as providing the most comprehensive and highest-quality micro data available on U.S. household assets and debts. The survey collects detailed household-level data on assets and liabilities and on demographic characteristics, income, employment and pensions, credit market experiences, and expectations and attitudes. The data are reported as of the time of the interview, except for income, which refers to the prior calendar year. These variables are summarized in Table 1, Panel A and described in the Online Appendix.[9]

Vehicles are a large part of family's durable consumption basket, and the SCF asks detailed questions on up to four vehicles that the family owns, and we primarily rely on vehicle ownership to measure status consumption.[10] The detail found in the SCF vehicle questions (including the make, model, and model year of the vehicle) helps us measure status along a number of different dimensions.[11] Although the absence of other consumption data in the SCF is a limitation, cars are widely viewed as the canonical status good. For example, the statistical evidence in Heffetz (2011) indicates that strangers are more likely to notice a household's atypical expenditures on cars more than nearly any other expenditures and that expenditures on cars are highly elastic. Also, it is well known that since their introduction, the marketing and selling of cars have been inextricably tied to status as much as transportation (McShane 1995, Johansson-Stenman and Martinsson 2003, Sundie et al. 2011).

The SCF data also include information that can be used to help measure a household's expectations about

Table 1. Summary Statistics and County-Level Correlations

Panel A: SCF summary statistics

Variables	Mean	SD
Dependent variables (credit)		
ln(*Credit Card Balances*)	3.68	4.09
ln(*Total Debt Payments*)	5.27	3.03
ln(*Total Debt Level*)	8.69	4.62
ln(*Nonhousing Debt Level*)	6.34	4.49
Equity Share in Portfolio	0.29	0.33
Dependent variables (autos)		
Age of Newest Auto (yrs.)	1.75	0.76
ln(*Avg. Value of Automobiles*)	9.11	0.72
ln(*Highest-Value Automobile*)	9.16	0.79
Indicator for High-Status Auto	0.15	0.35
Independent variables		
Income Rank in Census Tract	0.57	0.27
IHS(*HHd. Normal Inc.*)	11.72	0.92
ln(*Tract Med. Income*)	10.89	0.44
ln(*Tract Med. House Value*)	12.17	0.67
Assets	738,661	3,879,133
Debts	116,010	271,029
Pct. with Recent Unemp. Spell	0.17	0.38
Pct. Denied Credit	0.17	0.38
Pct. Paying > 40 pct. of Income to Debt Repayment	0.11	0.31
Spending Equaled Income	0.27	0.44
Spending Was Less Than Income	0.57	0.49
Pct. Married	0.63	0.48
Avg. Number of Kids	0.86	1.16
Pct. Urban	0.82	0.38
Pct. Renter	0.26	0.44
Age (percentage of family heads)		
Age < 35	0.20	0.40
Age 35–44	0.20	0.40
Age 45–54	0.22	0.41
Age 55–64	0.17	0.38
Age 65–74	0.11	0.31
Age > 75	0.10	0.29
Race/ethnicity (percentage of family heads)		
White	0.76	0.43
Black	0.11	0.31
Latino	0.09	0.29

Panel B: Correlation of high-status cars and demographics

Variable	Correlation
Population Density	0.39
Urban Population (%)	0.41
Median Income	0.51
Gini Coefficient	0.28
Poverty Rate	–0.15
Black Population (%)	0.22

Notes. Weighted means of pooled 2004-2010 SCF demographic variables are shown. Variables in this table are those of the baseline regression model (column (2) of Table 2, Panel A), plus select variables used in other regressions. As such, these summary statistics represent car-owning families. This table reports the correlations between the average fraction of high-status cars bought in the county (2002–2010) and select county demographic variables. All correlations are significant at the 1% level.

its permanent income. In particular, when enquiring about income, the SCF requires respondents to note whether their total income is unusually high or low relative to a normal year (i.e., windfall income). If income was unusually high or low, then a follow-up question is asked about what the family's income is in a typical year. This "normal" family income measure, then, should be a measure of income that smoothes away transitory income shocks and can approximate the family's permanent income.[12] The SCF asks how the family's income has fared over the past five years relative to inflation and how the family expects their income to progress relative to inflation over the upcoming year. Income expectations are a key part of the permanent income hypothesis, so including a measure in our regression models will be important.

The SCF data also allow us to include other possible determinants of consumption behavior. The level of assets and debts, as well as dummies for net worth percentiles, may impact these choices. We can also control for the race of the head of the family, which has been shown elsewhere to be an important factor in consumption choices (Charles et al. 2009).[13]

We also observe other potentially important characteristics of the family (age of the head, marital status, number of kids, etc.) as well as an urban/nonurban classifier. Access to credit markets, recent unemployment, and other measures of financial strain may also impact a family's ability to signal through spending on visible status goods. And the SCF data allow us to include controls for families that were recently denied credit, have recently experienced an unemployment spell, or are carrying a debt burden such that debt servicing makes up more than 40% of family income.[14] The SCF data also allow us to measure the time that a family has spent in and around its current residence. Specifically, we can measure the number of years that the family head (or spouse) has lived within 25 miles of the current residence and how recently the family moved into its current residence.

2.2.2. American Community Survey Data on Neighborhood Income. The internal SCF data include data on the census tract of residence for each family, and we create a measure of income rank in a census tract by linking the SCF data with summary census tract income measures from the ACS. The 2005–2009 ACS provides census tract-level data on the overall number of households and the number of households within 16 income buckets: less than $10,000; $10,000–$14,999; $15,000–$19,999; $20,000–$24,999; $25,000–$29,999; $30,000–$34,999; $35,000–$39,999; $40,000–$44,999; $45,000–$49,999; $50,000–$59,999; $60,000–$74,999; $75,000–$99,999; $100,000–$124,999; $125,000–$149,999; $150,000–$199,999; and $200,000 or more (in 2009 dollars).

To construct a measure of each family's income rank in the census tract, we use the SCF measure of the household's total income and place that family in one of the 16 income bins from the ACS data. We then compute the fraction of households within the tract that earns *less* than the SCF family, taking the average within bins. An example can make this concrete. Consider a reference family that earns $110,000. Assume that there are 100 families inside the tract and that 60 families earn less than $100,000. Assume further that there are 10 families with an income in the $100,000–$124,999 bin. We do not know where the reference family's income lies within this bin, so we compute the reference family's income rank as the average of the cases where the other nine families in the bin are either above or below the reference family's income. That is, if the other nine families are all below the reference family's income, then its rank is 69/100; if the nine families in the bin all have incomes higher than $110,000, then the reference family's rank is 60/100. In the baseline specification, we use the average of these two values to measure rank: 64.5/100. Alternative definitions—using just the fraction of households in the tract that earn less or more, or assuming a uniform distribution within the income bin—do not qualitatively change the results that follow.[15]

2.2.3. Polk Automobile Data. For each county in the United States, Polk records the number of new cars sold by make and model. Using this information, we compute the fraction of high-status cars sold in each county over the period 2002–2010. A high-status car is defined as a near-luxury or luxury car as classified by Kelley Blue Book.[16] Figure 2 shows that in the aggregate, the mean fraction of new cars sold that were classified as high status or luxury rose steadily over the decade, from about 4.2% in 2002 to about 5.3% in 2010, with only a small drop during the financial crisis in 2008. Table 1, Panel B reports the simple correlations between the fraction of high-status cars bought in a county and a number of demographic variables. The fraction of high-status cars is positively correlated with income inequality, as well as the median income in the county. These cars are more likely to be bought in more urban counties and in areas with high population density.

3. Main Results

This section presents estimates of Equation (1) using household-level data from various waves of the SCF throughout the 2000s. We measure status using a household's income rank relative to its census tract neighbors. This variable equals 0 if the household's income is in the lowest percentile, 0.1 if it is at the 10th percentile, and extends up through 1, which indicates that the household is in the top decile of the income distribution within the census tract. Status goods, such as luxury cars, are often bought using debt, and we first examine the impact of a household's income rank on various dimensions of the household's credit usage and portfolio choices. We then use the detailed data on automobiles in the SCF to examine the relationship between income rank and car characteristics.

3.1. Credit

Table 2, Panel A estimates the impact of a household's income rank on the log of the household's credit card balance using pooled cross sections of the 2004, 2007, and 2010 waves of the SCF. Standard errors are clustered at the state level, but the results remain similar when clustered at the tract level, and these are available upon request. Column (1) controls linearly for the household's "normal" or permanent income, as well as the median income in the census tract along with state fixed effects; the latter absorbs nonparametrically state-level differences in credit regulations, social norms, and state-level factors that might affect the use of credit card debt and a household's income rank. The evidence is consistent with the signaling hypothesis.

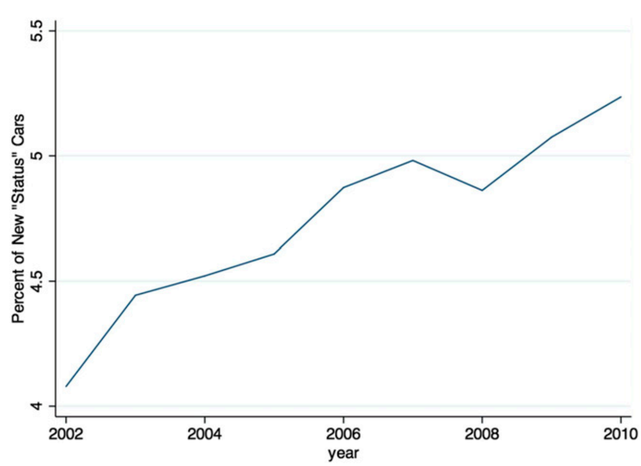
The coefficient on the household's income rank is significant, positive, and economically large. A 1-standard-deviation increase in a household's income rank is associated with a 0.23-standard-deviation increase in the log of credit card balances.[17] Evaluated at the mean credit card balance in the sample, this increase in rank suggests a $3,200 increase in credit card balances. This magnitude conflates both the extensive and intensive margins, as many households have no credit card balances. The implied effect among households with positive balances—the intensive margin—suggests a $2,700 increase in balances. Column (1) also shows that higher absolute income households tend to have lower credit card balances. In this case, a 10% increase in normal income is associated with a 6.9% drop in credit card balances. Households in higher-income census tracts, in part on account of better credit access, also tend to have higher balances.

Endogenous selection into census tracts is a potential source of bias. Column (2) uses the rich detail in the SCF to include a large number of household-level and tract controls that might determine both credit usage and tract-level income rank. These controls include a mix of demographic and economic variables: age, race, marital status, number of children, urban status, quartics of assets and debt, unemployment spells, and renter status. The baseline specification also includes measures of credit constraints such as an indicator for whether the debt payment to income ratio exceeds 40%; an indicator for whether the person was recently turned down for credit; and measures for whether annual spending in the previous year was greater than, less than, or equal to income.

Beyond these individual-level controls, the local cost of housing could also bias the income rank coefficient. Households sort into neighborhoods in part because of local amenities such as parks, schools, and access to jobs. This sorting can lead to higher house prices in census tracts with more amenities and inelastic housing supply (Saiz 2010). But for those households that select into a high-cost tract, the household's higher debt service burden could also shape its credit card balances differently at different points in the income distribution. This could help explain the results in column (1). For example, households that are poorer relative to their neighbors in an expensive census tract—lower income rank—might have less debt capacity to invest in status goods and hence maintain lower credit card balances. In addition to median income in the census tract, then, the baseline also includes the median census tract house price. From column (2), we see that whereas these controls attenuate the coefficient on the normal income variable, there is little change in the income rank coefficient.

Another potential confounding explanation stems from the idea that income could affect consumption decisions nonlinearly. Column (3) focuses on this possibility, controlling for income using a fourth-order polynomial. The point estimate on income rank is little changed.[18] Income expectations could also be an important omitted variable. Households anticipating a rapid rise in future income might move into census tracts where their current income might be well below the neighborhood's median income; these aspirational households might also be less able to afford status goods (such as a high-status car), trading off the benefits of consuming neighborhood amenities versus the ability to signal status using consumer debt.

Figure 2. (Color online) Percentage of New High-Status Cars Sold in the United States



Note. This figure plots the fraction of "high-status" cars bought in the United States using data from Polk.

Table 2. Tract Income Rank and the Role of Credit, 2004–2010 Pooled SCF

Panel A: Effect of income rank on credit card balances (log)

Variable	(1) No additional controls	(2) Baseline controls	(3) Nonlinear income	(4) Expect.	(5) Peers
Income Rank in Census Tract	3.942***	3.512**	3.332**	3.484**	3.519**
	(0.375)	(0.415)	(0.255)	(0.430)	(0.415)
IHS(HHd, Normal Inc.)	−0.694**	−0.122		−0.116	−0.120
	(0.101)	(0.105)		(0.106)	(0.105)
ln(*Tract Med. Income*)	1.043**	1.168**	1.112**	1.159**	1.131**
	(0.169)	(0.151)	(0.134)	(0.152)	(0.151)
Controls	No	Yes	Yes	Yes	Yes
R^2	0.031	0.168	0.169	0.169	0.169
N	13,327	13,327	13,327	13,327	13,327

Panel B: Effect of income rank on other financial outcomes

	Total Debt Payments (log)	*Total Debt Level* (log)	*Nonhousing Debt level* (log)	*Filed for Bankruptcy*	*Equity Share in Portfolio*
Variable	(1) Baseline controls	(2) Baseline controls	(3) Baseline controls	(4) Baseline controls	(5) Baseline controls
Income Rank in Census Tract	3.024**	4.202**	4.690**	0.052**	0.192**
	(0.211)	(0.318)	(0.397)	(0.025)	(0.023)
IHS(HHd, Normal Inc.)	0.201**	0.188**	−0.071	0.003	−0.001
	(0.057)	(0.083)	(0.102)	(0.006)	(0.008)
ln(*Tract med, income*)	1.248**	1.701**	1.873**	0.048**	0.089**
	(0.109)	(0.169)	(0.198)	(0.014)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes
R^2	0.43	0.398	0.263	0.123	0.268
N	13,327	13,327	13,327	13,327	13,327

Notes. Standard errors reported are in parentheses, are clustered at the state level, and are adjusted for imputation uncertainty. SCF data are imputed five times; reported coefficient estimates are the mean across the five implicates. Baseline controls include a wide range of household demographic variables (age, race, marital status, children, urban status, etc.), economic variables (inverse hyperbolic sine (IHS) of normal income, quartics of assets and debt, unemployment spells, renter status, etc.), measures of credit constraints (debt payment to income ratio > 40%; recently turned down for credit; and measures of whether annual spending in the year prior was greater than, less than, or equal to income), and local variables (log of tract median income, log of median tract house price, and state dummies).

***and ** denote significance at the 1% and 5% levels, respectively.

That is, rather than signaling, these results could be driven by the nexus of income expectations and the neighborhood location decision. Fortunately, the SCF asks households both about their income expectations and about past income realizations relative to inflation. The survey also collects data on a households' general sentiment or optimism about the future path of the economy.[19] These expectations are likely to shape both moving decisions and the purchase of large consumer durables, and we include these measures of income and aggregate economic expectations in column (4). The results are again unchanged relative to the baseline specification, suggesting that the signaling motive is still quite strong even after accounting for a household's expected future economic prospects.

There is evidence that peer effects feature in important economic decisions, and these effects could also be a source of bias (Bertrand et al. 2000, Grinblatt et al. 2008). Households living in areas with more high-status cars might also be induced to buy these cars. And to the extent that the percentage of high-status cars in the local area is correlated with relative household income, this type of peer effect could lead to a spurious association between relative income and debt. Column (5) uses the Polk data to control for the fraction of high-status cars in the county bought over the past decade—we do not have this information at the tract level. This point estimate, available upon request, is insignificant, and the coefficient on income rank remains unchanged.

The evidence in Coibion et al. (2014) suggests that local inequality might matter for debt decisions, and available upon request are results that control for inequality inside the tract; the main results remain unchanged. Available upon request are also results that control for whether the respondent or spouse is an entrepreneur: self-employed in a partnership or manages his or her own business. The results are unchanged, suggesting that they are not solely an artifact of some types of occupational choices. In what follows we use the specification in column (2), which controls for the potentially important household socioeconomic variables as the baseline specification.

Using this baseline specification, Table 2, Panel B examines the impact of income rank on other dimensions of credit usage. We also find that rank affects these other dimensions of credit usage. The dependent variable in column (1) is the log of a household's total debt service payments. The coefficient on income rank is positive and significant, and a one-standard-deviation increase in income rank is associated with a 70% increase in a household's monthly debt service—this is about a $900 increase for the typical household. Column (2) uses the log of a household's total outstanding stock of debt, including consumer and mortgage debt. There is again evidence of a significant positive relationship between rank and the stock of debt. Mortgage debt might endogenously reflect a household's preference for certain types of neighborhood amenities, and column (3) uses the stock of nonhousing debt. The income rank point estimate is little changed.

The previous evidence suggests that signaling behavior might drive the use of credit card and other types of consumer debt. There is also more general evidence in the literature that households that use credit card debt might be more prone to bankruptcy (Domowitz and Sartain 1997). Building on this more general link between credit card debt and bankruptcy, column (4) examines whether income rank and the signaling motive might be associated with whether a household has ever filed for bankruptcy. We find that a 1-standard-deviation increase in income rank is associated with a 0.045-standard-deviation or 1.5-percentage-point increase in the probability that the household has filed for bankruptcy.

Status considerations could also explain the heterogeneity in portfolio riskiness across households. Households with high income rank might, for example, hold riskier assets in order to generate higher returns and afford visible status goods. To investigate this hypothesis, column (5) of Table 2, Panel B uses the share of a household total equities to the value of household total financial assets as the dependent variable. It is well known that wealthier households tend to have riskier portfolios, and we continue to control for the baseline demographic and economic variables (Table 2, Panel A, column (2)), including household net worth. The coefficient on income rank is positive and significant at the 1% level. It suggests that a 1-standard-deviation increase in income rank is associated with a 4.6-percentage-point or 0.15-standard-deviation rise in the share of equity in the household's portfolio.

Unobserved attitudes to risk taking might drive these portfolio decisions and also increase a household's income relative to its neighbors. The SCF directly asks households about their risk preferences.[20] And in results available upon request, we include answers to these questions. The point estimate on income rank decreases slightly but remains significant at the 1% level.[21]

We have included a large number of observables to control for endogenous selection and various hard-to-measure attitudes toward risk and future income. But despite the persistence of these results across a number of very different specifications, it remains possible that the income rank results might be an artifact of unobserved factors that determine both selection into a census tract and household behavior. In this subsection, we make use of the 2007–2009 SCF panel in order to develop tests that can control for time-invariant household preferences. This special panel unfortunately does not ask detailed questions about car ownership, but it does include the standard credit variables and portfolio variables. Another caveat is that although the panel absorbs time-invariant household preferences, the data were collected at the peak of the financial crisis and ensuing credit crunch, and this could affect the estimates when using the credit usage variables.

From Table 3, in all cases the income rank variable is positive, and it is statistically significant in four out of five cases. From column (2), a one-standard-deviation increase in the change in income rank is associated with a 13% increase in debt service payments.[22] And despite the contraction in household credit supply and household deleveraging during this period, the effects of income rank on debt levels, both inclusive and exclusive of mortgage debt (columns (3) and (4)), remain significant. Likewise, whereas equity prices swung sharply over this period, greater income rank is associated with a greater share of equity in household financial assets. Credit card credit lines were cut sharply over this window, falling from $21,500 to $20,000 among those that managed to retain credit lines, and the income rank coefficient is not significant at conventional levels when using the credit card balance as the dependent variable (column (1)). Taken together, the evidence suggests that income rank and the incentive to signal status through conspicuous consumption might drive credit and portfolio decisions. We next turn to car ownership to provide more direct evidence of this hypothesis.

3.2. Cars

Cars are the canonical signaling good, and the SCF measures a household's cars along several useful dimensions.

Table 3. The 2007–2009 SCF Panel

Difference in...	(1) *Credit Card Debt* (log)	(2) *Total Payments* (log)	(3) *Total Debt* (log)	(4) *Nonhousing Debt* (log)	(5) *Fraction of Equity in Total Financial Assets*
Income Rank Census Tract	0.654	0.658**	1.200**	1.355**	2.182**
	(0.487)	(0.290)	(0.421)	(0.443)	(0.620)
ln(*Household Normal Income*)	−0.056	−0.002	−0.046	−0.047	0.020
	(0.052)	(0.037)	(0.056)	(0.053)	(0.081)
Controls	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.05	0.03	0.01	0.10
N	3,839	3,839	3,839	3,839	3,839

Notes. Standard errors are reported in parentheses, are clustered at the state level, and are adjusted for imputation uncertainty. SCF data are imputed five times; reported coefficient estimates are the mean across the five implicates. Controls include changes in asset levels and change in household circumstances (children, mobility, marital status, etc.).

**denotes significance at the 5% level.

Table 4 pools together the various cross-section waves, and we first estimate the impact of income rank on the log of the highest value of the cars owned by a household using the baseline specification. From column (1) of Table 4, a one–standard-deviation increase in income rank is associated with a 17% increase in the value of a household's most expensive car. As before, we perturb this specification by controlling for "normal" income nonlinearly (column (2)), expectations about future income growth (column (3)), and the ownership of status cars among geographically proximate neighbors (column (4)). The impact of income rank on the maximum value remains positive and statistically significant across these specifications.

Cars can convey status and prestige along a number of different dimensions. A relatively new car aimed at the mass market might be more expensive than a used "prestige" or "luxury" brand car but still signal less status than the used prestige brand. Similarly, owning multiple expensive cars might be seen as an even more powerful signal of relative wealth rather than owning a number of cars whose combined average value might be lower. Therefore, given the nuance surrounding status indicators, the remaining columns of Table 4 examine the impact of income rank on the car ownership decision along some of these different dimensions.

Column (5) of Table 4 uses the Kelley Blue Book definitions to create an indicator variable that equals 1 if the household owns a luxury or "near-luxury" brand—a high-status car. Using the same reference data source, column (6) computes the average value of all cars owned by the household. Column (7) focuses instead on the average age of the household's car. A common pattern emerges. Income rank is positively

Table 4. Relative Income Rank and Car Purchase Attributes, 2004–2010 SCF (Pooled)

	Highest Value Car (ln)				*Nice Car*	*Avg. Val.* (ln)	*Age* (yrs.)
Variable	(1) Baseline controls	(2) Nonlinear income	(3) Expect.	(4) Peers	(5) Baseline controls	(6) Baseline controls	(7) Baseline controls
Income Rank in Census Tract	0.614**	0.810**	0.607**	0.617**	0.050	0.522**	−0.581**
	(0.069)	(0.034)	(0.069)	(0.068)	(0.032)	(0.060)	(0.065)
	[0.217]				[0.036]	[0.202]	[−0.207]
IHS(*HHd. Normal Inc.*)	0.088**		0.087**	0.088**	0.029**	0.090**	−0.054**
	(0.024)		(0.025)	(0.024)	(0.010)	(0.023)	(0.020)
ln(*Tract Med. Income*)	0.362**	0.425**	0.359**	0.348**	0.007	0.316**	−0.350**
	(0.036)	(0.027)	(0.036)	(0.037)	(0.015)	(0.032)	(0.040)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.361	0.359	0.361	0.362	0.156	0.291	0.246
N	13,329	13,329	13,329	13,329	13,329	13,329	13,226

Notes. Standard errors are reported in parentheses, are clustered at state level, and are adjusted for imputation uncertainty. SCF data are imputed five times; reported coefficient estimates are the mean across the five implicates. Shown in brackets are the coefficient interpretations; a one–standard-deviation change in *Income Rank in Census Tract* is associated with a [.] standard deviation change in the column dependent variable. Baseline controls include a wide range of household demographic variables (age, race, marital status, children, urban status, etc.), economic variables (inverse hyperbolic sine (IHS) of normal income, quartics of assets and debt, unemployment spells, renter status, etc.), measures of credit constraints (debt payment to income ratio 40%; recently turned down for credit; and measures of whether annual spending in the year prior was greater than, less than, or equal to income), and local variables (log of tract median income, log of median tract house price, and state dummies).

**denotes significance at the 5% level.

associated with the probability of owning a high-status car and the average value of the cars owned by the household. It is also negatively associated with the age of the household's cars: higher income rank households are more likely to own newer vehicles. A 1-standard-deviation increase in income rank implies a 3.6–percentage-point rise in the probability of owning a status car, a 14.5% rise in the average value of all cars, and a 15.8% drop in the age of the household's youngest car. Even along these distinct but related dimensions, then, there is evidence that relative income might affect the decision to invest in signaling goods.

3.2.1. Tenure and Income. Examining the length of time that a household has lived in a neighborhood—its tenure in the neighborhood—can both help gauge the extent to which these results might be driven by endogenous selection and also reveal better how mobility and uncertainty might shape signaling behavior. Forecasting relative income over long periods of time can be difficult. And households that have lived in a census tract for a long period are less likely to have selected into the tract based on unobserved factors that determine both their relative income expectations at the time of entry and their subsequent car-buying behavior. Also, households that have lived in a neighborhood for a long time are likely to already be part of local social networks and may thus have a weaker incentive to engage in costly signaling behavior.

The first two columns of Table 5 examine how tenure in the neighborhood mediates the effects of rank on the value of a household's most expensive car. In particular, the SCF reports how long each household has lived at its current address, and column (1) of Table 5 uses this tenure information to restrict the sample to those households that have lived in the census tract for more than 20 years. Controlling for age and the baseline variables, the effect of relative income remains significant, and it is about two-thirds the baseline estimate reported in column (1) of Table 4; the point estimate is about the same if the sample is restricted to those households residing in the neighborhood for more than 10 years (available upon request). The point estimates are about two times as large when restricting the sample to only those households that have moved into the tract within the last 5 years (column (2)). Hence, for households that have recently moved, as well as those that are less mobile, there is evidence of signaling behavior, suggesting that selection based on unobserved variables is unlikely to be the principal explanation for these results.

We have seen evidence that income rank might determine both credit usage outcomes and the consumption of status goods such as cars. However, the signaling hypothesis would predict that rank might impact these decisions especially for the higher-income households. Notably, an exogenous increase in the number of poor inside a census tract lowers both the average income in the tract and the unconditional probability that any household is high income. Higher-income households thus have a stronger incentive to signal status through visible consumption purchases. Compounding this result is the fact that credit is generally cheaper and more available for higher-income households. Thus, higher-income households that also rank highly in the local income distribution likely have both a greater incentive and borrowing capacity to purchase more expensive cars. To test this hypothesis, column (3) interacts the rank variable with a household's normal income.

The interaction term is significant, suggesting that the effect of rank on signaling behavior might be higher among richer households. For a household at the median normal income level of about $60,000, moving from the 25th to the 75th percentile in rank is associated with a $2,697, or 34%, increase in the value of the household's most expensive car. But for a household with a normal income of about $150,000, presumably having both the incentive and credit access to buy status cars, a similar increase in rank is associated with a $3,150, or 38%, increase in the value of the most expensive car.

4. Aggregate Evidence

The previous correlations suggest that the desire to signal status might drive credit decisions and the purchase of visible consumption goods such as luxury cars. An implication of this individual-level evidence is that the consumption of visible status goods might be lower in geographic areas where incomes are known to be homogeneous. But an influx of poor households into the zip code or county that increases the local dispersion of income can now make it worthwhile for richer households to purchase status cars to signal their higher relative income rank. This intuition suggests that an increase in income inequality in a geographic area might be associated with an increase in the fraction of status cars bought in the area—the county or zip code.

Evaluating this prediction is, however, sensitive to the underlying source of the variation in income inequality within the geographic area. An increase in income heterogeneity from an influx of poor can increase the consumption of visible status goods by the rich. Likewise, in more complex signaling models where signaling—the purchase of luxury cars—is a convex function of income, then income redistribution among the existing population that increases inequality will also elicit an increase in the consumption of high-status cars. But if this function is concave, then a redistribution of local income that

Table 5. Extensions: Income Rank and Neighborhood Tenure, with Interactions

Variable	At least 20 years	Less than 5 years	Baseline + interaction
Income Rank in Census Tract	0.331**	0.713**	–0.119
	(0.119)	(0.112)	(0.359)
ln(*Household Normal Income*)	0.080**	0.062	0.076**
	(0.034)	(0.041)	(0.026)
ln(*Tract Median Income*)	0.293**	0.451**	0.348**
	(0.071)	(0.056)	(0.034)
Interaction: *Income Rank in Census Tract* by ln(*Household Normal Income*)			0.059*
			(0.030)
R^2	0.356	0.375	0.362
N	2,574	5,274	13,329

Notes. Standard errors are reported in parentheses, clustered at the state level, and are adjusted for imputation uncertainty. SCF data are imputed five times: reported coefficient estimates are the mean across the five implicates. All models include baseline controls as in Tables 2 and 4. The model with natural log of car with highest value as dependent variable is shown here, and the results are qualitatively similar for the other three dependent variables explored in Table 4.

**and * denote significance at the 5% and 10% levels, respectively.

increases inequality can yield the opposite outcome: a decrease in the consumption of high-status cars (Glazer and Konrad 1996). It is also important to note that a positive correlation between inequality in a county and the fraction of high-status cars does not identify whether higher-income individuals in more unequal counties use luxury cars to signal their rank or whether it is the less affluent that buy these cars in unequal counties to keep up with the Joneses.

With these limitations in mind, we study the relationship between county-level income inequality and the purchase of high-status cars. Polk gives us the make and model for each car sold in the county, and we use the Kelley Blue Book's definition of near-luxury and above models to identify high-status cars, computing the ratio of high-status to total cars sold in the county within a calendar year as our dependent variable of interest. We observe these data annually from 2002 to 2010. The inequality and other county-level observables are available at two points in time: from the U.S. census in 2000 and from the ACS in 2005–2009. The ACS data are sampled over the period 2005–2009 and are considered accurate over this sampling period. The empirical strategy matches the Polk data over the period 2002–2004 with the 2000 census, and it uses the ACS data for the 2005–2009 period.[23]

Column (1) of Table 6, Panel A regresses the high status ratio, observed in 2002, on the Gini coefficient in the county computed from the 2000 census. State fixed effects, which control for potentially important state-level factors, such as the state gas tax, and other state government-imposed costs on car ownership, such as registration fees and emission requirements, are the only additional controls. The Gini point estimate is statistically and economically significant, suggesting that a 1-standard-deviation increase in inequality is associated with a 0.4–percentage-point or 0.16-standard-deviation increase in the fraction of high-status cars purchased in the county.

Column (2) controls for a number of potentially important socioeconomic factors. The fraction of high-status cars is likely to be higher in richer counties, and we control for the log of median income in the county as well as the fraction of residents below the poverty line. Demographic factors such as the log population, area, urbanization, and the racial composition of the county are also likely to be important. These variables enter with intuitive signs. A 1–standard-deviation increase in median income is associated with a 0.53-standard-deviation increase in the fraction of high-status cars bought in the county; these types of cars are also less likely to be purchased in more urban, and presumably more congested, counties. The coefficient on inequality is about double that in column (1) and remains significant at the 1% level.

Columns (3)–(10) repeat this exercise for the period 2003–2010. This period spans the boom in consumption and house prices, the rise of securitization in auto financing and the extension of subprime credit, and the financial crisis and the Great Recession. Recall that for 2005–2010, the county-level data are drawn from the ACS. Despite these differences across the sample period, the impact of inequality on the ratio of high-status cars bought in the county remains significant and is largely unchanged.

Although the county-level evidence helps gauge the potential aggregate impact of the status motive on consumption, it also raises a number of identification challenges not present in the more detailed household-level data. In the presence of credit market frictions, rising inequality could, for example, disproportionately limit credit access for those at the bottom of the income distribution, leading to a large bifurcation in the types of cars bought inside a highly unequal county. Apart from credit market frictions, car purchases are often

Table 6. Inequality and the Fraction of High-Status Cars

Panel A: County-level regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variable	2002	2002	2003	2004	2005	2006	2007	2008	2009	2010	2002–2010
Income Inequality	0.127***	0.408***	0.438***	0.451***	0.405***	0.422***	0.453***	0.432***	0.434***	0.468***	0.0476**
	(0.041)	(0.047)	(0.050)	(0.053)	(0.054)	(0.051)	(0.056)	(0.056)	(0.058)	(0.059)	(0.021)
Obs.	3,057	2,949	2,953	2,948	2,859	2,870	2,869	2,864	2,855	2,857	5,873
R^2	0.319	0.701	0.686	0.697	0.641	0.599	0.647	0.61	0.626	0.632	0.974

Panel B: Instrumental variables, county-level regressions

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	*First-Stage Income Inequality*	*Fraction of High-Status Cars*		*Median Household Leverage in County, 2006*	
Variable		IV	OLS	IV	OLS
Land Inequality, 1930	0.0286***				
	(0.007)				
Income Inequality		0.681**	0.517***	23.89***	1.804***
		(0.302)	(0.055)	(9.770)	(0.599)
Observations	2,994	2,992	2,992	2,148	2,148
R^2	0.558		0.685		0.626

Notes. Standard errors are clustered at the state level: In Panel A, all columns include state fixed effects. Columns (2)–(10) include population, land area, median income, black population, white population (all in logs), and the fraction of the population below the poverty line and the fraction of urban population. For column (11), we average the status ratio over the two subperiods 2002–2004 and 2005–2010, and then we regress the change in the ratio of high-status cars over these two periods on the change in inequality and the other covariates. Column (11) also includes county fixed effects. In Panel B, all regressions include state fixed effects, population, land area, median income, black population, white population (all in logs), and the fraction of the population below the poverty line and the fraction of urban population. All variables are averaged over the period 2002–2010. Land inequality in 1930 is the Gini coefficient based on the distribution of farm sizes in 1930. From column (1), the F-statistic that the *Land Inequality, 1930* variable is 20.84 (p-value = 0.00).

***and ** denote significance at the 1% and 5% levels, respectively.

amortized over a number of years, and differences in expectations of income growth for those at different points in the income distribution could also explain these results. Likewise, microtargeted advertising that steers some buyers to certain brands could also help account for some these results.

It is also possible that county time-invariant factors, such as the local industrial structure, perhaps as determined by weather or local geography, might drive both inequality and the types of cars available for purchase in a county, helping to explain some of these results. Also, the historic location of car dealership networks could also affect the supply of certain types of luxury models, leading to a potentially spurious association between inequality and the fraction of high-status cars bought in a county. That is, many high-status cars are imported, with well-developed dealership and parts distribution networks along the coasts, lowering the cost of ownership. At the same time, economic activity and migration patterns along the coasts could independently lead to a more unequal income distribution in those areas, inducing a positive relationship between inequality and the fraction of high-status cars that is unrelated to the signaling hypothesis.

To address some of these concerns, column (11) constructs a panel based on the U.S. census and ACS data, allowing the use of county-level fixed effects to absorb nonparametrically these potentially important time-invariant factors. We average the status ratio over the two subperiods 2002–2004 and 2005–2010, and then we regress the change in the ratio of high-status cars over these two periods on the change in inequality and the other covariates. At this level of spatial disaggregation, both inequality and the ratio of high-status cars are highly persistent. In the case of the former, the correlation across the two periods is 0.69 at the county level, whereas in the case of high-status cars, the correlation is 0.94. Also, including county fixed effects absorbs some of the mediating mechanisms, such as culture and social norms, through which inequality might affect signaling behavior. Despite these factors, the evidence in column (11) continues to suggest that an increase in inequality within a county is significantly associated with an increase in the ratio of high-status cars. The point estimate implies that a 1-standard-deviation increase in inequality is associated with a 0.06-standard-deviation rise in the ratio of high-status cars.

We now exploit some of the historic determinants of inequality to gauge further the robustness of these results. This approach is motivated by the fact there is already substantial evidence both in the United States and elsewhere that some economic and social forces can be highly persistent. For example, segregation changed dramatically over the 20th century, yet Cutler et al. (1999) show that the relative segregation of different cities remained highly persistent, with the correlation across cities between segregation in 1890 and segregation in 1990 as high as 50%. In a similar vein, Acemoglu et al. (2001) and Engerman and Sokoloff (2002) provide international evidence on the persistence of important economic and political institutions. Building on these ideas, we instrument county-level inequality averaged over 2002–2010 with the inequality in farm holdings observed in 1920.

Counties with more unequal farm holdings in the early 20th century tended to spend far less on education and other redistributive public goods, and there is evidence that elites in these counties were better able to use their relative political power to restrain both the provision of public goods and financial development (Ramcharan 2010; Rajan and Ramcharan 2011, 2016). Less public redistribution and more limited access to private credit are both likely to limit social mobility and lead to persistent inequality within a county (Galor et al. 2009).

Interesting in its own right, the first-stage regression in column (1) of Table 6, Panel B supports the idea that whereas the United States has experienced substantial social and economic change over time, the cross-sectional variation inequality remains highly persistent.[24] Column (1) uses the Gini coefficient of income inequality averaged over 2002–2010 as the dependent variable, and includes the standard suite of conditions on the standard suite of demographic and economic controls, as well as state fixed effects. The point estimate on the Gini coefficient of farm holdings in 1920 is positive and significant at the 1% level. A 1-standard-deviation increase in this variable is associated with a 0.08-standard-deviation increase in income inequality averaged over 2002–2010.

Column (2) of Table 6, Panel B regresses the fraction of high-status cars sold in the county averaged over 2002–2010 on contemporary inequality, with the latter instrumented using land inequality in 1920. Exploiting the variation in farm land inequality from 1920—a period that largely predates the expansion of the automobile—the instrumental variables (IV) point estimate is statistically significant at the 1% level and large. A 1-standard-deviation increase in contemporary inequality is associated with a 0.67-standard-deviation increase in the fraction of high-status cars sold over the decade; this magnitude is slightly larger than the corresponding ordinary least squares (OLS) estimate reported in column (3).

We have already seen household evidence linking the signaling hypothesis to the use of consumer credit. Using data on the median household leverage ratio for 2006 in each county (Mian and Sufi 2011), we examine this prediction at the county level. The point estimate is positive and significant at the 1% level, and it suggests that a 1-standard-deviation increase in inequality is associated with a 0.10-standard-deviation increase in household leverage within the county (column (4)). Unobserved factors that increase inequality, such as limited access to credit, could also lead to lower leverage, and these OLS estimates could be biased downward.

The IV point estimate in column (5), which uses the historic variation in inequality, is about 10 times larger. This evidence suggests that the dispersion incomes might matter for the consumption of luxury goods and debt. Household leverage encompasses the overall stock of consumer debt, including mortgage debt, accumulated over many years. And the relatively large IV point estimate in this specification, in part, reflects the effects of measurement error when using inequality at a given point of time. In turn, the historic variation in inequality likely captures the effects of inequality and signaling behavior on a range of credit choices over time.

5. Conclusion

This paper has investigated the importance of the status concerns in the consumption and financial decisions of households. Using the SCF linked with census tract information from the ACS, we find evidence that a household's income rank relative to its close neighbors—those in the same census tract—is positively associated with the decision to buy a high-status car. After controlling for income itself, as well as a number of other demographic and economic variables, income rank is also positively associated with credit usage, including credit card balances, the decision to file for bankruptcy, and riskier portfolios. The aggregate county-level evidence also appears consistent with the signaling hypothesis. Income inequality at the county level is positively associated with both the fraction of high-status cars bought in the county and indicators of consumer leverage.

These results suggest that the signaling motive might feature in some durable goods consumption choices, as households invest in status consumption goods to signal that they might have advanced in their relative income position compared with their close neighbors. And when taken together, these findings also suggest that rising inequality might have broader macroeconomic consequences, including a reduced savings rate and greater household debt. We leave it to future research to quantify better the aggregate implications of income heterogeneity.

Acknowledgments

The authors thank Andreas Fuester, Diana Hancock, Nick Roussanov, Michael Palumbo, Wayne Passmore, John Sabelhaus, and seminar participants at various institutions for useful comments. The analysis and conclusions set forth are those of the authors and do not indicate concurrence by other members of the research staff or the Board of Governors of the Federal Reserve System.

Endnotes

[1] The literature on the economic and political consequences of inequality is large. See, for example, Acemoglu and Robinson (2011), Ramcharan (2010), Rajan (2010), Rajan and Ramcharan (2011), and Piketty (2014).

[2] There is a long tradition in the social sciences noting that concerns about social status might influence credit and consumption decisions (Veblen 1899, Duesenberry 1949). The recent evidence is also compelling. See also Heffetz (2011), as well as seminal contributions by Frank (1984, 1985). Using a range of different methods, other fields such as evolutionary biology, anthropology, and marketing have collected evidence suggesting that conspicuous consumption and the accumulation of symbolic capital might shape human behavior. Redistributive feasts—such as weddings in South Asia and funerals in Polynesia—as well as the making of large unrequited transfers might, for example, be driven by a desire to signal social status and rank within local hierarchies (Bliege Bird et al. 2001, Bliege Bird and Smith 2005).

[3] Conversely, Agarwal et al. (2017) find that bankruptcies adversely affect not only the consumption of the bankrupt but also the consumption of the nearby neighbors in the same building as well. Agarwal et al. (2019) examine these issues within the context of warranty claims.

[4] Other important recent contributions in this area include De Giorgi et al. (2020). In very different settings, Kuhn et al. (2011) and Angelucci and De Giorgi (2009) also show that changes in income can affect the consumption and credit decisions of nearby peers. Social status concerns have also been used to explain portfolio decisions—see, for example, Demarzo et al. (2004), Hong et al. (2004), and Grinblatt and Keloharju (2001). And there is also evidence that relative income differences among neighbors and colleagues might even influence subjective measures of well-being and job satisfaction (Luttmer 2005, Card et al. 2012).

[5] The literature in economics on both the selection into neighborhoods and the importance of neighborhoods in shaping outcomes is large. See, for example, Case and Katz (1991), Borjas (1995), Cutler and Glaeser (1997), Cutler et al. (1999), Rhode and Strumpf (2003), Hong et al. (2004), and the references contained therein.

[6] A one-standard-deviation increase is about 25 percentiles.

[7] See Bricker et al. (2012) for detailed summary information about the 2010 SCF.

[8] The SCF employs a dual-frame sample design, including a multistage area-probability (AP) sample and a list sample. The AP sample, which comprises roughly 60% of the total sample, provides broad national coverage and was selected by the National Opinion Research Center at the University of Chicago (see Tourangeau et al. (1993)). The list sample oversamples households that are predicted to be relatively wealthy based on a model of wealth (see Kennickell (2017), Kennickell and McManus (1993), and Bricker et al. (2017)). The two components of the sample are combined to represent the population of households. The eligible respondent in a given household is the economically dominant single individual or the financially most knowledgeable member of the economically dominant couple. Most of the questions in the interview of that sample were focused on the "primary economic unit," a concept that includes the core individual or couple and any other people in the household (or away at school) who were financially interdependent with that person or couple.

[9] We should emphasize that the publicly released SCF data are cleaned of any identifying information about the responding family, including any geographic information about the family. The Federal Reserve does release summary information by census region, though (see Bricker et al. (2012)). The empirical analysis in this paper uses the internal SCF data in order to identify the household's state, county, and census tract of residence.

[10] After the fourth vehicle, only general questions (such as the worth of the vehicles) are asked.

[11] These details are encoded and run through the National Automobile Dealers Association guide to obtain an estimated value of each vehicle. The value of a vehicle, then, is not directly based a self-reported car value, though it is based on self-reported characteristics of each vehicle. The aggregate value of vehicles in the SCF closely matches the National Income and Product Accounts (NIPA) aggregate car stock value, so we have reason to believe that these car values (and reported car traits) are high quality. We note that the vehicle data collected in the 2009 wave of the 2007–2009 SCF panel collects a self-reported value of all vehicles owned by the household, limiting the SCF panel's usefulness in determining changes in vehicle ownership.

[12] See Krimmel et al. (2013, p. 357): "The concept of 'normal' income in the SCF is conceptually and empirically close to the concept of 'permanent' income that economists generally consider when they describe consumer behavior. The label 'normal' stems from a question posed to SCF respondents; after they report their actual income, they are asked whether they consider the current year a 'normal' year. If respondents state it is not a normal year, they are asked to report a value for 'normal' income. Actual and normal income are the same for most respondents. However, Ackerman and Sabelhaus (2012) show that the deviations from normal for the subset who report such deviations provide a relationship between actual and permanent income consistent with estimates of transitory shocks using panel income data."

[13] Specifically, we use indicators for households in the lowest quartile of the net worth distribution, in the 25th to 50th percentiles, the 50th to 75th percentiles, the 75th to 90th percentiles, and the top decile.

[14] Included among families denied credit are those who responded that they did not apply for credit because they believed they would be turned down. Earlier studies, including Jappelli (1990) and Duca and Rosenthal (1991), have found the SCF questions about credit applications and outcomes provide a useful indicator of households that are credit constrained. Krimmel et al. (2013) use the same 40% threshold to indicate risky levels of leverage among SCF households. Recent regulations given by the Consumer Financial Protection Bureau give a similar debt service to disposable income ratio of 43% in the context of regulating "qualified mortgages" (see http://files.consumerfinance.gov/f/201308_cfpb_atr-qm-implementation-guide_final.pdf, last accessed June 5, 2015).

[15] For households with incomes above the $200,000 bucket, this income rank variable is potentially mismeasured. However, this affects only 2% of the households in our sample, and we also show that our main results are robust when income rank is measured far more coarsely as household income relative to the median income in the census tract.

[16] These brands include Acura, Aston Martin, Audi, Bentley, BMW, Cadillac, Infiniti, Lamborghini, Land Rover, Lexus, Lincoln, Lotus, Maserati, Maybach, Mercedes-Benz, Porsche, Rolls-Royce, Tesla, and Volvo.

[17] One standard deviation in income rank is about 25 percentiles.

[18] Available upon request are results that model income nonparametrically within a semiparametric model—the results are little changed.

[19] The precise questions are as follows: "Over the past five years, did your total (family) income go up more than inflation, less than inflation, or about the same as inflation?" (for X304), "Over the next year, do you expect your total (family) income to go up more than inflation, less than inflation, or about the same as inflation?" (for X7364), and "I'd like to start this interview by asking you about your expectations for the future. Over the next five years, do you expect the U.S. economy as a whole to perform better, worse, or about the same as it has over the past five years?" (for X301).

[20] The question is, "Which of the statements on this page comes closest to the amount of financial risk that you (and your {husband/wife/partner}) are willing to take when you save or make investments?"

1. *Take substantial financial risks expecting to earn substantial returns.
2. *Take above average financial risks expecting to earn above average returns.
3. *Take average financial risks expecting to earn average returns.
4. *Not willing to take any financial risks.

[21] A determined skeptic may dismiss the value of these survey based questions. There is, however, some evidence that survey responses are correlated with economic choices (Puri and Robinson 2007).

[22] One standard deviation of the 2007–2009 change in income rank is about 20 percentiles.

[23] Note that the 2004, 2007, and 2010 SCF surveys use the 2000 decennial census definitions of tract borders. Only the 2005–2009 ACS data use the 2000 census tract definitions and have statistics at the census tract level. Gini coefficient data used in our analysis at the county level come from the 2006–2010 ACS because the 2005–2009 ACS does not have county-level Gini data, and county definitions do not change each decade. All ACS data and subsequent results are presented in inflation-adjusted 2010 dollars to remain consistent with the 2010 SCF cross section.

[24] The correlation coefficient between expenditures per pupil at the county level in 1920 and 1994 is 0.92.

References

Acemoglu D, Robinson J (2011) *Why Nations Fail: The Origins of Power, Prosperity and Poverty* (Crown Publishing Group, New York).

Acemoglu D, Johnson S, Robinson J (2001) The colonial origins of comparative development: An empirical investigation. *Amer. Econom. Rev.* 91(5):1369–1401.

Ackerman S, Sabelhaus J (2012) The effect of self-reported transitory income shocks on household spending. Finance and Economics Discussion Series 2012-64, Board of Governors of the Federal Reserve System, Washington, DC. Accessed July 1, 2014, http://www.federalreserve.gov/pubs/feds/2012/201264/201264pap.pdf.

Agarwal S, Mikhed V, Scholnick B (2020) Does the relative income of peers cause financial distress? Evidence from lottery winners and neighboring bankruptcies. *Rev. Financial Stud.* 33(1):433–472.

Agarwal S, Qian W, Zou X (2017) Thy neighbor's misfortune: Peer effect on consumption. Preprint, submitted November 13, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2780764.

Agarwal S, Chomsisengphet S, Scholnick B, Zhang M (2019) Salient peers and consumption: Evidence from the warranty claims of neighbors. University of Alberta School of Business Research Working Paper 2019-708, University of Alberta, Edmonton, AB, Canada.

Akerlof GA, Kranton RE (2000) Economics and identity. *Quart. J. Econom.* 115(3):715–753.

Angelucci M, De Giorgi G (2009) Indirect effects of an aid program: How do cash transfers affect ineligibles' consumption? *Amer. Econom. Rev.* 99(1):486–508.

Bagwell LS, Bernheim BD (1996) Veblen effects in a theory of conspicuous consumption. *Amer. Econom. Rev.* 86(3):349–373.

Bertrand M, Morse A (2016) Trickle-down consumption. *Rev. Econom. Statist.* 98(5):863–879.

Bertrand M, Luttmer EFP, Mullainathan S (2000) Network effects and welfare cultures. *Quart. J. Econom.* 115(3):1019–1055.

Bliege Bird R, Smith EA (2005) Signaling theory, strategic interaction, and symbolic capital. *Current Anthropol.* 46(2):221–248.

Bliege Bird R, Smith EA, Bird DW (2001) The hunting handicap: Costly signaling in human foraging strategies. *Behav. Ecology Sociobiol.* 50(1):9–19.

Borjas GJ (1995) Ethnicity, neighborhoods, and human-capital externalities. *Amer. Econom. Rev.* 85(3):365–390.

Bricker J, Bucks B (2016) Negative home equity, economic insecurity, and household mobility over the Great Recession. *J. Urban Econom.* 91(January):1–12.

Bricker J, Henrique A, Moore K (2017) Updates to the sampling of wealthy families in the survey of consumer finances. Finance and Economics Discussion Series 2017-114, Board of Governors of the Federal Reserve System, Washington, DC. Accessed March 1, 2018, https://doi.org/10.17016/FEDS.2017.114.

Bricker J, Kennickell A, Moore K, Sabelhaus J (2012) Changes in U.S. family finances from 2007 to 2010: Evidence from the Survey of Consumer Finances. *Federal Reserve Bull.* 98(2):1–80.

Campbell JY (2006) Household finance. *J. Finance* 61(4):1553–1604.

Campbell J, Cochrane J (1999) By force of habit: A consumption based explanation of aggregate stock market behavior. *J. Political Econom.* 107(2):205–251.

Card D, Mas A, Moretti E, Saez E (2012) Inequality at work: the effect of peer salaries on job satisfaction. *Amer. Econom. Rev.* 102(6):2981–3003.

Carroll CD (1997) Buffer-stock saving and the life cycle/permanent income hypothesis. *Quart. J. Econom.* 112(1):1–55.

Case AC, Katz LF (1991) The company you keep: The effects of family and neighborhood on disadvantaged youths. NBER Working Paper No. w3705, National Bureau of Economic Research, Cambridge, MA.

Charles K, Hurst E, Roussanov N (2009) Conspicuous consumption and race. *Quart. J. Econom.* 124(2):425–467.

Coibion O, Gorodnichenk Y, Kudlyak M, Mondragon J (2014) Does inequality lead to more household borrowing? New evidence from household data. NBER Working Paper No. 19850, National Bureau of Economic Research, Cambridge, MA.

Cronk L (2005) The application of animal signaling theory to human phenomena: Some thoughts and clarifications. *Soc. Sci. Inform.* 44(4):603–620.

Cutler D, Glaeser E (1997) Are ghettos good or bad? *Quart. J. Econom.* 112(3):827–872.

Cutler DM, Glaeser EL, Vigdor JL (1999) The rise and decline of the American ghetto. *J. Political Econom.* 107(3):455–506.

De Giorgi G, Frederiksen A, Pistaferri L (2020) Consumption network effects. *Rev. Econom. Stud.* 87(1):130–163.

Demarzo P, Kaniel R, Kremer I (2004) Diversification as a public good: Community effects in portfolio choice. *J. Finance* 59(4):1677–1715.

Domowitz I, Sartain RL (1997) Determinants of the consumer bankruptcy division. *J. Finance* 54(1):403–420.

Duca J, Rosenthal S (1991) An econometric analysis of borrowing constraints and household debt. Federal Reserve Bank of Dallas Research Paper 9111, Federal Reserve Bank of Dallas, Dallas.

Duesenberry JS (1949) *Income, Saving, and the Theory of Consumer Behavior* (Harvard University Press, Cambridge, MA).

Dupor B, Liu W-F (2003) Jealousy and equilibrium overconsumption. *Amer. Econom. Rev.* 93(1):423–428.

Engerman SL, Sokoloff KL (2002) Factor endowments, inequality, and paths of development among new world economics. NBER Report No. w9259, National Bureau of Economic Research, Cambridge, MA.

Frank RH (1984) Are workers paid their marginal products? *Amer. Econom. Rev.* 74:549–71.

Frank RH (1985) The demand for unobservable and other nonpositional goods. *Amer. Econom. Rev.* 75(1):101–116.

Frank RH (1989) Frames of reference and the quality of life. *Amer. Econom. Rev.* 79(2):80–85.

Galor O, Moav O, Vollrath D (2009) Inequality in landownership, the emergence of human-capital promoting institutions, and the great divergence. *Rev. Econom. Stud.* 76(1):143–179.

Georgarakos D, Haliassos M, Pasini G (2014) Household debt and social interactions. *Rev. Financial Stud.* 27(5):1404–1433.

Glazer A, Konrad KA (1996) A signaling explanation for charity. *Amer. Econom. Rev.* 86(4):1019–1028.

Grinblatt M, Keloharju M (2001) How distance, language, and culture influence stockholdings and trades. *J. Finance* 56(3):1053–1073.

Grinblatt M, Keloharju M, Ikaheimo S (2008) Social influence and consumption: Evidence from the automobile purchases of neighbors. *Rev. Econom. Statist.* 90(4):735–753.

Han YJ, Nunes JC, Drèze X (2010) Signaling status with luxury goods: The role of brand prominence. *J. Marketing* 74(4):15–30.

Heffetz O (2011) A test of conspicuous consumption: Visibility and income elasticities. *Rev. Econom. Statist.* 93(4):1101–1117.

Hong H, Kubik JD, Stein JC (2004) Social interaction and stock market participation. *J. Finance* 59(1):137–163.

Jappelli T (1990) Who is credit-constrained in the U.S. economy? *Quart. J. Econom.* 105(420):219–234.

Johansson-Stenman O, Martinsson P (2006) Honestly, why are you driving a BMW? *J. Econom. Behav. Organ.* 60(2):129–146.

Kennickell A (2017) Modeling wealth with multiple observations of income: Redesign of the sample for the 2001 Survey of Consumer Finances. *Statist. J. IAOS* 33(1):51–58.

Kennickell A, McManus D (1993) Sampling for household financial characteristics using frame information on past income. Working paper, Federal Reserve Board, Washington, DC.

Kőszegi B, Rabin M (2007) Reference-dependent risk attitudes. *Amer. Econom. Rev.* 97(4):1047–1073.

Krimmel J, Moore KB, Sabelhaus J, Smith P (2013) The current state of U.S. household balance sheets. *Federal Reserve Bank St. Louis Rev.* 95(5):337–359.

Kuhn P, Kooreman P, Soetevent A, Kapteyn A (2011) The effects of lottery prizes on winners and their neighbors: Evidence from the Dutch postcode lottery. *Amer. Econom. Rev.* 101(5):2226–2247.

Kuminoff NV, Smith VK, Timmins C (2013) The new economics of equilibrium sorting and policy evaluation using housing markets. *J. Econom. Literature* 51(4):1007–1062.

Loewenstein G, O'Donoghue T, Rabin M (2003) Projection bias in predicting future utility. *Quart. J. Econom.* 118(4):1209–1248.

Luttmer EFP (2005) Neighbors as negatives: Relative earnings and well-being. *Quart. J. Econom.* 120(3):963–1002.

McShane C (1995) *Down the Asphalt Path: The Automobile and the American City* (Columbia University Press, New York).

Mian A, Sufi A (2011) House prices, home equity-based borrowing, and the US household leverage crisis. *Amer. Econom. Rev.* 101(5): 2132–2156.

Piketty T (2014) *Capital in the Twenty First Century* (Harvard University Press, Cambridge, MA).

Puri M, Robinson D (2007) Optimism and economic choice. *J. Financial Econom.* 86(1):71–99.

Rajan RG (2010) *Fault Lines: How Hidden Fractures Still Threaten the World Economy* (Princeton University Press, Princeton, NJ).

Rajan RG, Ramcharan R (2011) Land and credit: A study of the political economy of banking in the United States in the early 20th century. *J. Finance* 66(6):1895–1931.

Rajan R, Ramcharan R (2016) Constituencies and legislation: The fight over the McFadden Act of 1927. *Management Sci*. 62(7): 1843–1859.

Ramcharan R (2010) Inequality and redistribution: Evidence from U.S. counties and states, 1890–1930. *Rev. Econom. Stat.* 92(4): 729–744.

Rhode PW, Strumpf KS (2003) Assessing the importance of Tiebout sorting: Local homogeneity from 1850 to 1990. *Amer. Econom. Rev.* 93(5):1648–1677.

Roussanov N (2010) Diversification and its discontents: Idiosyncratic and entrepreneurial risk in the quest for social status. *J. Finance* 65(5):1755–1788.

Saiz A (2010) The geographic determinants of housing supply. *Quart. J. Econom.* 125(3):1253–1296.

Sundie JM, Kenrick DT, Griskevicius V, Tybur JM, Vohs KD, Beal DJ (2011) Peacocks, Porsches, and Thorstein Veblen: Conspicuous consumption as a sexual signaling system. *J. Personality Soc. Psych.* 100(4):664–680.

Tourangeau R, Johnson R, Qian J, Shin H-C, Frenkel M (1993) Selection of NORC's 1990 National Sample. Working paper, National Opinion Research Center at the University of Chicago, Chicago.

Veblen T (1899) *The Theory of the Leisure Class: An Economic Study of Institutions* (B. W. Huebsch, New York).