Big Brands, Big Cities: How the Population Penalty Affects Common, Identity Relevant Brands in Densely Populated Areas

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Big Brands, Big Cities: How the Population Penalty Affects Common, Identity Relevant Brands in Densely Populated Areas

ABSTRACT

The population density of a geographical area has a well-known and strong positive effect on sales in the area. Yet, for some brands, there may be factors that affect the strength of this density-sales relationship. The present research shows that for product categories that consumers use to signal their identities (e.g., clothing, restaurants and cars), the strength of this relationship varies with brand commonness. Consumers residing in densely populated areas are motivated to express their distinctiveness by reducing their preference for identity relevant brands that are common, such as large chains and brands owned by many people. Thus, as identity-relevant brands become more common, they suffer from a "population penalty" – a weakening of the positive effect of population density on sales. We show this effect with three experiments and two empirical analyses of automobile and alcohol sales. Our findings extend literature on distinctiveness theory by demonstrating these effects at the community level and provide insights for marketers on accounting and adjusting for this effect.

Keywords: population; sales; brand commonness; distinctiveness; affiliation; sub-branding

The population density of a given area is an important criterion in many marketing decisions because, ceteris paribus, greater density offers a larger potential market. But an important consideration for many marketers is how the strength of this density-sales relationship varies. One such moderator is suggested by work in social psychology that considers the process through which individuals derive identity based on social groups (c.f., Brewer 1991; Brewer and Weber 1994). Put simply, humans wrestle with "…a fundamental tension between…needs for validation and similarity to others (on the one hand), and a countervailing need for uniqueness and individuation (on the other)" (Brewer 1991, p. 477). This tension prompts individuals to seek an optimal balance of these forces, and thus a large, depersonalized social setting can activate a need for distinctiveness (Brewer and Weber 1994). As a consequence, living in a densely populated metropolitan area could prompt an individual to make purchase decisions that enable them to express their unique self-identity, leading them to avoid purchasing more ubiquitous brands.

Building on literature demonstrating that consumers often signal their distinctiveness by avoiding common brands of identity relevant products (Ariely and Levav 2000; Berger and Heath 2007), our research examines how the population density where consumers reside can affect such preferences. Specifically, we expect consumers residing in densely populated areas would show less interest in common brands than those residing in sparsely populated areas. Thus, population density should simultaneously increase the number of potential customers while also altering their brand preferences. Therefore, the relationship between population density and sales should be weaker for common brands than uncommon brands. This moderating effect, which we refer to as the “population penalty,” should be limited to brands such as clothing and music that are relevant to consumer’s identities and are typically used to communicate about identities (Berger and Heath 2007).

A recent analysis of chain versus non-chain retailers by the Census Bureau seems to show evidence of this population penalty. Jarmin, Klimek and Miranda (2009) examined all U.S. retail locations from 1976-2000 to determine the likelihood of a location ceasing its operations. Chain (i.e., common) retailers were observed to be slightly, but consistently, more likely to cease operations of their locations in metropolitan areas than rural areas, whereas retailers with a single location were slightly *less* likely to cease operations in metropolitan areas than rural areas (Jarmin, Klimek and Miranda 2009). Although these findings suggest the potential of a generalized moderating effect of brand commonness, they are inadequate for investigating the underlying process and ruling out other explanations. In this research, we seek to overcome these limitations and offer a theory-based investigation of whether brand commonness moderates the relationship between population density and performance.

We aim to make several contributions. First, our findings document a modest, but significant, downward pressure on sales that goes above other well-known dampening effects, such as cannibalization and competition (Ghosh and Craig 1991) and may lead marketers for certain brands to overestimate potential sales in densely populated areas. Second, we demonstrate a psychological underpinning for these findings grounded in optimal distinctiveness (Brewer 1991), which provides theoretical insight as well as guidance for practitioners in understanding why the population penalty occurs. Third, we demonstrate the robustness of this effect, with its occurrence being observed through experimental manipulation of population, investigation of actual population from an experimental respondent's area of residence, and through secondary data and measures of population density.

POPULATION AND PERFORMANCE

Sales of a brand in a particular area are determined by many variables, including competition, sales efforts, and pricing, among others (Cottrell 1973; Ingene and Lusch 1980; Liu 1970; Walters and MacKenzie 1988). The demographic characteristics of the residents of an area are also an important consideration for marketers, including factors such as marital status, age and per capita income (Pol and Thomas 1997; Reinartz and Kumar 1999). But one of the most important factors is the size (or density) of the population. Theory has long recognized the link between sales and the surrounding population (Christaller 1933; Craig et al. 1984; Goodchild 1984; Huff 1962). This link has been well established empirically with findings consistently indicating that sales increase when the surrounding population grows (Ferber 1958; Ingene and Lusch 1980; Ingene and Yu 1981; Kumar and Karande 2000; Liu 1970; Pauler, et al. 2009). For example, Reinartz and Kumar (1999) conclude from a study of grocery stores that population measures are a stronger predictor of sales than are characteristics of the store, consumer type or level of competition.

Population and the Need for Distinctiveness

To extend this research on the population-sales link, we turn our attention to factors that moderate it. One such moderator is suggested by literature on population density. According to optimal distinctiveness theory, individuals have competing needs to maintain both individual and collective identities, and they often balance these needs through their connection to social groups that provide in-group social affiliation as well as inter-group distinctiveness (Brewer 1991; Brewer, Manzi and Shaw 1993). For instance, teenagers characteristically adopt fashions and tastes similar to their peers, but distinct from their parents (Brewer 1991). However, social groups vary in their ability to fulfill these needs. Specifically, large social groups, which tend to be inclusive and indistinct, do a poor job of satisfying the need for a distinct identity, prompting a strong desire among group members to fulfill this need in other ways (Brewer, Manzi and Shaw 1993).

To test these predictions, Brewer and Weber (1994) assigned students to either large or small social groups. Next, participants viewed a video of another group member, discussing his/her abilities in various domains (e.g., academic, artistic, athletic, etc.), and finally participants evaluated themselves by rating their own abilities in the same domains. The size of the social group influenced whether the participant's self-evaluations were alike or different from the other in-group member. When participants were assigned to a small social group, their self-evaluations were assimilated towards the student in the video, indicating a need to affiliate with group members. On the other hand, participants assigned to a large social group contrasted themselves away from the student in the video, suggesting a need for distinctiveness.

Similar effects may apply to population density at the community level (Brewer 1991; Torelli, et al. 2017). For decades sociologists have consistently found that urban residents are more heterogeneous than their rural counterparts (Wirth 1938), and are more likely to express unique attitudes and behaviors than rural residents (Fischer 1975, 1984). For instance, the large populations in urban areas exhibit greater religious heterogeneity than rural populations (Ogburn and Duncan 1964) and are more likely to adopt distinct cultural styles, such as avant-garde art, fads and fashions (Fischer 1975; Weber 1976).

Brand Commonness and the Population Penalty

Consistent with the findings that social group size affects consumer motivations to express their distinctiveness, we expect consumers residing in densely populated areas will show less interest in purchasing common brands for identity relevant products than consumers in sparsely populated areas. Individuals frequently pursue their need for distinctiveness (and affiliation) through their consumption preferences (Belk, Bahn and Mayer 1982; Lynn and Snyder 2002). They may use products to express their individuality (Kim and Drolet 2003) and behave in ways to disaffiliate from others unlike themselves, and with whom they do not wish to be associated (White and Dahl 2005). These tendencies can be both chronic (Snyder and Fromkin 1977) as well as context dependent (Berger and Heath 2007).

Thus, population density should affect consumer interest in the use of common, identity relevant brands to signal identity. Building on related concepts such as market presence (Stahl, et al. 2012) and majority preference (Ariely and Levav 2000; Berger and Heath 2007), we define *brand commonness* as the number of units associated with a particular brand in the marketplace at a given time. For durables, this relates to the units sold in the marketplace, while in a retailing context, brand commonness relates to the number of locations, ranging from uncommon retail brands, such as single site, colloquially “mom-and-pop shops,” to very common retail brands, such as large chain retailers with thousands of locations. As an objective measure, brand commonness offers implications for managerial decision-making, but consumers can perceive it, and their subjective views of the commonness of brands will drive their preferences.

In sum, we propose that the population density of an area will impact interest, purchase intentions and actual behavior towards common brands in product categories consumers typically use to express their identities. We expect population density will have an overall positive effect on sales, but for common brands of products that are identity relevant, these effects will be attenuated to a degree. In other words, common brands will suffer a "population penalty," by realizing less benefit from densely populated areas than their uncommon competitors. Formally, we propose the following hypotheses:

H1: Consumers who feel they are in areas with high population densities will have decreased interest and purchase intentions for common brands of identity relevant products, compared to uncommon brands.

H2: The perception of being in an area with high population density will activate a desire to distinguish the self from others, leading to decreased interest and purchase intentions for common brands of identity relevant products, compared to uncommon brands.

To test our predictions, we conducted five studies using a combination of experimental and empirical analysis methods. The first study demonstrates the basic effect by manipulating population density, and the second shows that the motivation for distinctiveness drives the effect. Study 3 tests the process by establishing that these effects occur for identity relevant categories (e.g. clothing stores) but not irrelevant categories (e.g. gas stations), demonstrating a boundary condition. In the final two studies, we test whether the individual level effects we hypothesize scale to market levels. We examine actual purchase behavior for two identity relevant product categories, showing a consistent interaction between population density and brand commonness indicative of the population penalty. We also include a difference-in-differences analysis based on an exogenous change in population density to provide further evidence for the causal ordering of the effects. We close with a discussion of the theoretical implications of the work, as well as some insights into how practitioners might adjust their behaviors in light of our findings.

STUDY 1

The purpose of study 1 was to provide initial evidence for our H1, by manipulating population density and observing consumers' hypothetical choices of an identity relevant product. Of course, manipulating actual population density is infeasible, but it is possible to simulate the psychological feeling of crowdedness. To accomplish this, we adapted a perceived population density manipulation from Sng, et al. (2017), where participants either read an article about population increases or a control article, and then selected a clothing store where they would shop, a category related to consumer identity (Heffetz 2011; Kamakura and Du 2012).

Method

The study employed a 2 level (population density: high, control) between-subjects design. One hundred forty-seven participants from the United States were recruited from the Amazon Mechanical Turk panel (Chandler, Mueller, and Paolacci 2014; Etkin, Evangelidis, and Aaker 2015; Pauwels, et al. 2016). Participants entered demographic information and were told that they were eligible for multiple studies, the first of which involved categorizing a news article. The articles, adapted from Sng, et al. (2017), served as the manipulation of perceived population density. Each article was presented in the style and format of *The New York Times* (full manipulations provided in Appendix A). In the high population density condition, the article was entitled "The Crowded Life: Too Many, Too Much," and discussed how high population densities in the United States were leading to overcrowding, long lines and traffic, and how cities were attempting to deal with these issues. In the control condition, the article was titled "Squirrel Explosion: Too Many, Too Much," and was similarly structured, describing growing populations of squirrels and how cities were attempting to deal with these issues. After reading the article, participants were asked to indicate which of several news categories applied to the article and to provide at least five keywords describing the article.

After completing the newspaper article task, participants were told that they would be completing a "Clothing Shopping Survey," and asked to imagine they were shopping for clothing in their area. Participants were offered a choice between four stores, all "offering similar selections and prices, but some are large chain stores and others are small independent stores." The names of the fictional stores were randomized, and were presented along with the total number of locations for each store. One of the store brands was very common (4,039 locations) and the other three were uncommon (3, 1, and 1 locations). The main dependent measure was the participants' choice of a common or uncommon store. After their choice, participants rated their agreement with the statements, "This is a common brand" and "I would encounter this brand frequently" for each of the four stores using seven-point scales (1 – Strongly disagree, 7 – Strongly agree), which were combined into measures of brand commonness ($r = .92$, $p < .01$).

Results and Discussion

Manipulation check. Participants rated the store with many locations as more common ($M = 6.09$) compared to the other stores ($M = 1.97$, $t(146) = 26.03$, $p < .001$), suggesting that the manipulation of brand commonness was successful.

As our dependent measure was dichotomous, we employed a logistic regression model with the population density manipulation as the independent variable and choice of a common brand as the dependent variable. The results of the regression revealed a significant effect of the population density manipulation ($\beta = -0.84$, $z = -2.31$, $p < .03$). Consistent with our H1, participants in the high-density condition were less likely to shop at the more common brand ($P = 23.9\%$) compared to those in the control condition ($P = 42.1\%$).

These results provide initial evidence for the effect of population density on interest in common brands. We observed that, as predicted, individuals who were made to feel as though population density was high chose less common brands compared to those in the control condition.

These results, however, provide little evidence for the underlying process resulting in these effects. In our H2 we hypothesized that, based on optimal distinctiveness theory, being in close proximity to others would create a desire to express a distinct identity. This desire should activate a disaffiliation motive, which leads individuals to avoid common brands. In our second study, we employ a moderation-of-process design (Spencer, Zanna and Fong 2005) to demonstrate this by manipulating affiliation and disaffiliation motives separately from population density.

STUDY 2

The purpose of study 2 was to expand on study 1 by providing evidence for the proposed optimal distinctiveness driven process. We also sought to generalize the results observed in study 1 to additional identity relevant product categories, coffee shops and furniture stores.

Method

The study employed a 2 (population density: low, high) x 3 (motive prime: control, disaffiliation, affiliation) x 2 (retail category: coffee shop, furniture store) mixed design, with population density and motive primes as between subjects factors and product category as a within subjects factor. One hundred seventy-three participants from the United States were recruited from Amazon's Mechanical Turk (average age: 35.8 years, 56.3% female). To disguise the purpose of the study, participants were told that they would be testing a new customer review website and were asked to imagine the area where they lived. In the sparse population density condition, they imagined "in a very short time that lots of people similar to you living in your area moved away, so that the population shrank to only ¼ of its current size." In the dense population condition, they imagined "in a very short time that lots of people similar to you moved into your area, so that the population grew to 4 times its current size." The statement specified that the others were "people similar to you" to strengthen the drive for distinctiveness intended by the manipulation. After reading the description, participants elaborated on the scenario by briefly writing how they would feel in a typical day in this environment.

To manipulate affiliation, participants completed a task adapted from Escalas and Bettman (2005). In the disaffiliation prime condition, they were asked to "think about a small, tightly-knit social group that you do not belong to and do not feel a part of. You should feel you are not this type of person and that you do not fit in with these people. This group should be quite specific, consisting of individuals who are very similar to one another." In the affiliation prime condition, participants were asked to "think about a small, tightly knit social group that you belong to and feel a part of. You should feel you are this type of person and that you fit in with these people. This group should be quite specific, consisting of individuals who are very similar to one another." Next, they wrote a brief statement about "how being an individual, separate from this group" (disaffiliation) or "how being associated with this group" (affiliation) would help them deal with the changes in the population of the area. In the control condition, participants did not read or respond to any additional information (see Appendix B).

After completing the manipulations of density and motive primes, participants rated their interest in shopping at four fictitious stores: two coffee shops and two furniture stores. The two stores from each category were presented as a set, with one of the stores being a common brand and the other uncommon. Brand commonness was manipulated by the number of retailer locations: common brands having more than 4,000 locations; uncommon brands had four or less. In a pretest drawn from the same population ($N = 57$), participants indicated how unique they perceived the stores to be (1 = Not at all unique, 7 = Very unique). A paired samples t-test indicated the store with many locations was perceived as less unique (*M* = 2.16) compared to the store with few locations (*M* = 5.02, $t(56) = 9.35$, $p < .01$). Each store was briefly described with a review containing the name of the store, a description of its products, a dollar-sign based rating of the retailer's pricing, a star-based rating of the retailer (both of the ratings were identical within the categories), and the number of retail locations. Our dependent variable was participants' rating of interest in shopping at both the common and uncommon brands (1 = Not at all, 7 = Very interested).

Results and Discussion

Manipulation Check. To verify the effect of the perceived population density manipulation, we coded the open-ended responses to the essay question asking participants what their lives would be like living in the area following the population change. Three research assistants, who were blind to the hypotheses of the study, coded the responses independently for mentions of crowds or busyness (e.g. "there would be longer lines"). The coders demonstrated a high level of agreement (Krippendorff's α = .86), and disputes were resolved by majority vote. Consistent with our expectations, participants in the high population density condition mentioned crowdedness at a higher rate (69.0%) compared to those in the low population density condition (1.1%, $\chi^2(1) = 88.72$, $p < .001$), suggesting that the manipulation of perceived population density was successful.

INSERT TABLE 1 HERE

Interest in Common Brands. Next, we analyzed participants' interest in shopping at the common stores. Our H2 predicted that the feeling of being in close proximity to others should activate a disaffiliation motive, which then leads consumers to avoid common brands. We therefore expected to observe an interaction effect of population density and the motive primes, with those in the control and disaffiliation conditions exhibiting lower interest in common brands for those who imagined living in a densely populated area compared with those who imagined a sparsely populated area, replicating the findings of study 1. However, we expected that this difference would be attenuated when participants were primed to affiliate. To test this, we employed a mixed model with density, motive, and their interaction as between subject effects, along with a repeated effect of category. This model revealed a marginal main effect of population density ($F(1, 315.04) = 3.15$, $p < .08$), qualified by the predicted interaction effect ($F(1, 315.04) = 5.34$, $p < .01$). Contrasts indicated that in the control condition, participants were more interested in shopping at the common brands when they imagined living in a sparsely populated area ($M = 4.79$) than in a densely populated area ($M = 3.91$, $t(315.04) = -2.61$, $p < .01$). In the disaffiliation condition, a negative effect of population density also emerged, with higher levels of interest in shopping at the common brands in sparsely populated areas ($M = 4.23$) than in the densely populated areas ($M = 3.71$, $t(315.04) = -2.21$, $p < .03$), consistent with the pattern observed in the control condition . However, in the affiliation condition, the difference between the population density conditions was not significant ($M_{\text{Sparse}} = 4.05$, $M_{\text{Dense}} = 4.54$, $t(315.04) = 1.62$, $p > .10$), supporting our prediction.

Interest in Uncommon Brands. For comparison, we analyzed interest in shopping at uncommon brand stores. For the uncommon brands, the same model revealed a significant main effect of motive prime ($F(1, 337.01) = 4.80$, $p < .01$). Compared to the control condition ($M = 4.13$), interest in shopping at the uncommon brands was higher in the affiliation condition (*M* = 4.60, $t(337.01) = -2.32$, $p < .03$) as well as in the disaffiliation condition (*M* = 4.68, $t(337.01) = -2.95$, $p <. 01$), but the affiliation and disaffiliation conditions did not differ ($t(337.01) = .53$, $p > .59$). More importantly, there were no other significant effects, indicating that the interest in the uncommon brands was not affected by the manipulation of density.

As predicted, interest in shopping at common stores depended on population density. In the control condition, when participants were given no motive prime, participants expressed lower purchase intentions for a common brand after thinking about living in a more densely populated area, thus replicating the findings of study 1 and supporting our H1. We observed the same results in the disaffiliation prime condition, but when participants were primed with affiliation, population density had no effect on shopping interest, supporting the proposition that high population densities create pressure to maintain a distinct identity, leading shoppers in such areas to avoid common chain stores. These results extend those of study 1, by providing a strong test of the process proposed in H2. Notably, we do not observe any effects on interest in shopping at uncommon brands, suggesting that the negative effect of population density on interest only occurs with common brands.

Having demonstrated the basic effect and provided evidence for the process in our first two studies, the goal of our third study was to test a theoretical boundary condition, the extent to which the product category was identity relevant. Prior research has shown that some product categories are more likely to be used by consumers to signal their identities to others (Berger and Heath 2007). The categories used in the first two studies – clothing, coffee and furniture – are all highly visible (Heffetz 2011; Kamakura and Du

2012), and thus individuals who perceive the area they live to be densely populated and are motivated to demonstrate their distinctiveness would be likely to chose products that help distinguish themselves from others. However, for other, less identity relevant categories, we expect that these effects would be attenuated. Formally, we propose the following hypothesis that will be tested in our third study:

H3: The effect of population density on interest and purchase intentions for common brands proposed in H1 will be moderated by the identity relevance of the product category, with the effect attenuated for less identity relevance categories.

STUDY 3

The purpose of the third study was to test our H3, establishing a boundary condition for our effect. We tested this proposition by having participants rate the likelihood of shopping at common and uncommon stores that were randomly assigned to be either clothing stores (high identity relevance) or gas stations (low identity relevance). Additionally, study 3 measured population density, rather than manipulating it as in the previous studies. This allowed us to test whether the effects of perceptions of density shown in the prior studies can also be observed with the actual experience of population density and to rule out other social identity processes, beyond those related to density.

Method

The study employed a 2 level (identity relevance: low, high) between subjects design, with population density as a measured factor. Two hundred forty-two respondents (average age: 35.6 years, 41.3% female) from the United States were recruited from the Amazon Mechanical Turk panel.

The overall procedure was similar to that of study 1. Population density was determined by geolocating participants using their IP addresses. Based on this, participants were assigned to counties, and county population density data was collected from the U.S. Census. Prior research suggests that population density would exhibit declining effects to scale (Sng, et al. 2017; Gelfand, et al. 2011), and we therefore log-transformed population density.

Participants were then randomly assigned to one of the two identity relevance conditions. In the high identity relevance condition, participants were told that they would be completing a “Clothing Shopping Survey,” as in study 1, while in the low identity relevance condition, participants were told that they would be completing a “Gas Shopping Survey.” Participants were presented with four generically named stores (e.g. “Store A,” “Station B”), along with the total number of locations for the brand. To clarify whether the effect was driven by avoidance of common brands, as we propose, or approach to uncommon brands, we included two common (both more than 1000 locations) and two uncommon brands (both with 1 location) among the four brands viewed by participants. As in study 1, the primary dependent measure was whether participants chose to shop at a common or uncommon brand. Participants then rated brand commonness using the same two items from Study 1 ($r = .96$, $p < .01$), and finally, participants rated the identity relevance of the product categories with two items adapted from Berger and Heath (2007): “To what extent do you think the following product categories contribute to self-expression, i.e. a person’s ability to express their identity?”

and “To what extent do you think people use the following product categories to make inferences about others, i.e. people think they know a lot about a person based on their choice in this domain?” These items were combined to form a measure of category identity relevance ($r = .88$, $p < .01$).

Results and Discussion

INSERT FIGURE 1 HERE

Manipulation checks. Participants rated the common stores as more common ($M = 6.49$) compared to the uncommon stores ($M = 3.13$, $t(241) = 33.09$, $p < .01$). Participants also rated the high identity relevant category (clothing stores) as more identity relevant ($M = 5.66$) than the low identity relevant category (gas stations, $M = 1.94$, $t(241) = 31.22$, $p < .01$), suggesting that the manipulations of brand commonness and identity relevance were successful.

Choice of common store. Next, we analyzed our dependent variable, choice of common store, using a binary logistic regression with county population density, dummy-coded identity relevance and their interaction as independent variables. There was a significant main effect of identity relevance ($\beta = 2.44$, $z = 2.58$, $p < .02$), qualified by the hypothesized interaction effect ($\beta = -.42$, $z = -2.16$, $p < .04$). As predicted, for the high identity relevant category, clothing stores, there was a negative effect of population density ($\beta = -.04$, $z = -2.02$, $p < .05$), while for the low identity relevant category, gas stations, population density did not have an effect on likelihood of choosing the common stores ($\beta = .03$, $z = 1.14$, $p > .25$).

The results of study 3 provide evidence for the effect of population, replicating the prior studies for high identity relevance products. Consistent with our H3, however, we did not observe these effects for a product category that was not identity relevant, demonstrating a theoretically consistent boundary condition.

Having presented a series of experimental studies offering evidence for the effect of population density on brand preferences in controlled settings using individuals and hypothetical choices, we now turn our attention to testing whether the population penalty can be observed in actual behavior at market-level scales. Here, population density should present two countervailing forces on sales of common, identity relevant brands – a greater number of customers but decreased interest in the brand due to the population penalty. The final two studies explore how these forces manifest using data on new car and alcohol sales, both product categories that are relatively visible (Heffetz 2011; Kamakura and Du 2012) and are identity relevant (Ariely and Levav 2000; Berger and Heath 2007; Southwick, et al. 1981).

STUDY 4

In this study, we explore the effect of the population penalty on a durable product – automobiles. Our model predicts a negative interaction effect of population density and brand commonness on brand sales, with commonness operationalized as the total number of cars on the road for each car brand.

Data and Models

The Car sales data used in the analysis were from the United Kingdom Department of Transport's annual licensing statistics from 2009 to 2014 for the 30 most popular brands (makes) of new cars (those registered for the first time) in each of the 11 administrative regions of the UK, which is the lowest level of analysis for which brand-specific data were available. The best selling car brand was Ford, with sales of approximately 292,000 new cars annually during this period; the lowest selling was Saab, with about 6,000 cars per year. Brand commonness was operationalized as the total number of cars on the road (not just new sales) in the UK. The analysis included the following variables:

$SALES_{irt}$ is the number of units sold as indicated by the number of first-time registrations of car brand *i* in region *r* in year *t*. The data is left truncated, as brands outside of the top 30 are aggregated in the original data. The top 30 car brands represent more than 99% of the passenger vehicles sold in the UK during the observed time period, suggesting that the truncation of the data is unlikely to introduce bias into the estimator, though it does limit our ability to observe any potential effects among very uncommon brands. To address this potential concern, we also present the results of a Tobit model in model (3) while excluding fixed effects (Greene 2004), for which the results are the same. Sales were log-transformed to reduce skewness.

DEN_{rt} is the estimated total population for region *r* for year *t*, divided by the size of the region in square kilometers. Population and area data are from the UK Office of National Statistics. As in study 3, density was log-transformed.

COM_{it} represents the commonness of the brand, measured as the total number of all cars for brand *i* registered across the entire UK in year *t*. This reflects all new and used registered cars of the brand that were operating on the road. We tested an operationalization of brand commonness using registered cars at the regional level and observed the same pattern of effects. Commonness was log-transformed.

We employed fixed effects estimators for this panel data set (Pancras, et al. 2012). The model including brand and region fixed effects allows us to capture all time-invariant observed and unobserved characteristics of each region and parent brands. We also include yearly fixed effects that capture idiosyncratic annual changes in the market. Thus, we estimated the model shown in equation (1) with fixed effects for brand μ_i, region μ_r, and time μ_t (Correia 2016), and employ robust standard errors clustered by region to address potential heteroskedasticity concerns.

$$SALES_{irt} = \beta_1 DEN_{rt} + \beta_2 COM_{it} + \beta_3 COM_{it} \cdot DEN_{rt} + \mu_i + \mu_r + \mu_t + \varepsilon_{irt} \quad (1)$$

We also employed a second model to address several potential concerns. One is due to the relationship between population density and income, which were correlated in our data ($r = .91$, $p < .001$). Because less common cars are likely to be more expensive, those living in densely populated regions might be more likely to purchase these less common cars instead of the less expensive, more common brands. Another concern is the effect of competition, with large numbers of competitor sales in more densely populated regions depressing sales for any individual brand. Thus, we modeled an alternative specification that includes controls for income, sale prices, and competitive sales.

$$SALES_{irt} = \beta_1 DEN_{rt} + \beta_2 COM_{it} + \beta_3 COM_{it} \cdot DEN_{rt} + \beta_4 INCOME_{it} + \beta_5 PRICE_{it} + \beta_6 COMP_{irt} + \mu_i + \mu_r + \mu_t + \varepsilon_{irt} \quad (2)$$

$INCOME_{rt}$ is the median gross annual income for region r during year t, which is included to control for effects of income levels and its influence on decisions to purchase more expensive makes of cars. Income data are from the UK Office of National Statistics.

$PRICE_{it}$, representing the average MSRP across models for new cars for brand i in year t. MSRPs for new car sales in Ireland were used as a proxy measure of prices. Price and income were each divided by 1,000 to ease interpretation.

$COMP_{irt}$ is the total sales of new cars in region *r* during year *t*, excluding the sales of brand i, which was included to capture the effect of competitor's car sales in the region. This value was divided by 1,000,000 to ease interpretation.

To reduce the influence of outliers in our analysis, all of the variables were Winsorized at the 99% level, though our results are unaffected by this transformation. For all models, the key test of our prediction is that the parameter β_3 should be significant and negative. Because our models involved interaction terms, there can be potential issues with multicollinearity, though this is to be expected as there is a structural relationship imposed by the interaction (McClelland, et al. 2017). Because our focus is on the interaction term and not broader macro issues relating to the overall model fit (Echambadi and Hess 2007), mean-centering our predictors can be used to alleviate this concern without impacting the estimates of the parameter of interest (Iacobucci, et al. 2016). The VIFs for the mean-centered variables were acceptable (all < 2.68), suggesting that multicollinearity was unlikely to affect our parameter estimates. We report results from the un-centered data to ease interpretation.

Results and Discussion

INSERT TABLE 2 HERE

INSERT TABLE 3 HERE

The descriptive statistics are presented in Table 2 and parameter estimates for all model specifications are presented in Table 3. The results for equation 1 demonstrate a significant relationship between brand commonness (the total number of cars of a given brand on the road) and brand sales for a given region ($\beta_2 = 1.074$, $p < .001$). More relevant to our research question, we observed a significant negative interaction between population density and brand commonness on a brand's sales (Model 1, $\beta_3 = -0.022$, $p < .001$). Consistent with our prediction, the effect of population density on regional sales of a particular car brand weakened as the brand became more common.

This effect was robust to controls for regional income, brand sale prices, and competitor sales (Model 2, $\beta_3 = -0.015$, $p < .05$), suggesting the effect is not driven by the relationship between higher population densities and higher incomes. We also observed the same effect in the Tobit model, which accounts for the left-censoring of the data (Model 3, $\beta_3 = -0.022$, $p < .001$). We present a summary of these and other robustness checks in Table 7 in Appendix D.

Consistent with the findings of our experimental studies, in real world data we observed that large brands experience a population penalty, realizing lower sales in densely populated areas. In our final study, we examine the population penalty using another real world data set in a different product context and country: the sales of alcohol at the level of individual bars and restaurants in Texas.

STUDY 5

The goal of our final study was to replicate the empirical findings of the prior studies in a different context, using an individual-level data set that would allow us to rule out a number of alternative explanations. We examine the interaction between population density and brand commonness on sales of alcoholic beverages from individual bar and restaurant locations. In addition to their noted visibility and identity relevance, this context is appropriate because such locations serve as an important social environment in many societies (Mandelbaum 1965).

In addition to replicating the results observed in study 4, this dataset also allowed us to consider several rival explanations including cannibalization, competition, distribution intensity, and endogeneity. First, cannibalization occurs when the opening of one store from the same brand negatively influences the sales of other same-branded stores in the area (Ghosh and Craig 1991; Kalnins 2004; Pancras, Sriram and Kumar 2012). Cannibalization is more likely to afflict common brands than uncommon ones because of their greater number, and is also more likely to occur in densely populated areas, since retailers often use the same population criteria in site selection for each location.

Second, sales are affected by competition. As with cannibalization, competing retailers are also likely to use high population density as a criterion to locate stores, and these increasing competitive pressures may lead to lower sales for those stores located in dense areas. We examine competition using both distance and sales based measures.

Third, we consider the effects of distribution by employing approaches adapted from prior work by Bucklin, Siddarth and Silva-Risso (2008) and Gielens, Gijsbrechts and Dekimpe (2014) to control for the effects of distribution intensity. Finally, we address endogeneity concerns through a natural experiment using an exogenous shock created by Hurricanes Katrina and Rita. The population displaced by the hurricanes increased the population density for certain regions in Texas more than others, allowing us to compare sales in these regions through a difference-in-difference analysis.

Data and Models

The data for this analysis come from a panel of alcoholic beverage sales for bars and restaurants in Texas maintained by the Texas Alcoholic Beverage Commission. The sales data exclude sales of food and other non-alcoholic products. Data were available monthly from January 2000 until December 2011, and in the main analysis were aggregated by year to match the time measurements for the population data. We removed sales from temporary events (e.g., charity fundraisers) and private club sales (e.g., fraternal organizations, conventions and catered events). During the observed period, there was considerable heterogeneity and change in county laws regarding sales of alcohol in Texas. Of the 254 counties, a number had legal restrictions on alcohol sales (e.g., “dry” or “damp” counties; Blumenthal 2003; Schadt 2001), leaving observations for 138 counties.

For each location, we identified its corresponding brand. We observed 11,271 bar and restaurant brands with 17,011 locations for an average of 1.51 locations per brand. Consistent with patterns at a national level, most brands (84%) had a single location in Texas; the most common brand, Chili’s Grill and Bar, had 122 locations in the state. For each location, there were an average of about six years of sales for a total of 101,779 observations. Sales measures include beer, wine and spirits but exclude food and other non-alcoholic items. The analysis included the following variables:

$SALES_{it}$ is the average monthly sales in dollars of alcoholic beverages for location *i* for year *t*. To avoid biases created by locations that had incomplete years of sales data (for example, a location that opened in the middle of a year), sales were averaged by the number of observed months. Sales were then log-transformed to correct for skewness.

DEN_{it} is the estimated population in year *t* in the county where location *i* was sited, divided by the square mileage of the county. These population estimates and square mileage are from the U.S. Census Bureau. As in the prior studies, the values were log-transformed.

COM_{it} reflects the total number of locations in the state of Texas in year *t* that were the same brand as location *i*, indicating commonness. Though our conceptualization of commonness is focused on broad areas, commonness could also be operationalized at the county level (reflecting a more localized experience with commonness), but our findings are the same for both levels of analysis. Brands were identified based on taxpayer identification number, alcohol permit information, and location names. Although taxpayer identification number is typically at a corporate or franchise level, we manually distinguished separate brands among these organizations. For instance, although Landry's, Incorporated owns many distinct brands such as Landry's Seafood, Morton's, and Fisherman's Wharf, the number of locations reflects the chain brand (e.g., Landry's Seafood) rather than the corporate brand (Landry's, Incorporated 2017) to better reflect customers' interactions with the brand. As in study 4, commonness was log-transformed.

The model included fixed effects for the brand, location, and county to capture their time-invariant observed and unobserved characteristics. We also include yearly fixed effects that capture idiosyncratic annual changes in the market. Thus, we estimated the model shown in equation (4) that includes fixed effects for particular restaurant locations μ_i, restaurant brand μ_j, county μ_k and year μ_t, again employing robust standard errors clustered by county.

$$SALES_{it} = \beta_1 DEN_{it} + \beta_2 COM_{jt} + \beta_3 COM_{jt} \cdot DEN_{kt} + \mu_i + \mu_j + \mu_k + \mu_t + \varepsilon_{it} \tag{4}$$

To test for issues involving the potential for the fixed effects to obscure some results, we also estimated this equation excluding all fixed effects (model 5). Further, we consider the effects of multiple alternative explanations through several sets of control variables. Following Bucklin, et al. (2008), we also consider the effects of cannibalization, competition and distribution intensity by including the following variables:

$AREALOC_{it}$ was the total number of locations of the same brand in the same county as location *i* at time *t*.

-$DIST1_{it}$ is the distance in miles between the focal location *i* and the nearest location of the same brand. As in prior work (Bucklin, et al. 2008), we reverse the sign and divide by 1,000 to ease interpretation. For those brands with only one location, this value was set to zero.

-$DIST10_{it}$ is the distance in miles between the focal location *i* and the 10^{th} nearest location of the same brand. Fifty-five brands had 10 or more locations, for those brands with fewer than 10 locations but more than two, the value was set to the distance to the furthest location, or zero if the brand only had two locations. The values were divided by 1,000 to ease interpretation. Because a substantial number of brands had fewer than three locations, we estimated our models limiting the analysis to only those brands with three or more locations to avoid potential issues with the imputation of zeros, and observed the same effects.

$-CDIST1_{it}$ is comparable to $-DIST1_{it,}$ but measures distance nearest location of any brand.

$-CDIST10_{it}$ is comparable to $-DIST10_{it}$, but measures the distance to the 10^{th} nearest location of any brand. These measures capture potential spatial competition, and were divided by 1,000 to ease interpretation.

$COMP_{it}$ is designed to capture local competition by representing the total number of competing bars and restaurants located in the same county as location *i* at time *t* (Campo, Gijsbrechts, and Nisol 2000; Dhar and Hoch 1997). We also tested operationalizations of competition scaled by population density and overall population, and observed no differences in our findings. These values were divided by 1,000 to ease interpretation.

HHI_{it} is the Herfindahl-Hirschman Index, which measures the overall concentration of an industry (Ordanini and Nunes 2016). Because our data include sales for each location, it is possible to calculate the individual market shares of each location. The HHI is calculated as the sum of squared market shares for each location in the same county as location *i* at time *t*, and ranges from 0.0 (representing a very competitive industry) to 1.0 (representing complete capture of the market by one store).

Using these variables we run various models, and for each model the key test is that the parameter β_3 is predicted to be significant and negative. We Winsorized all variables in our analysis at the 99% level, and mean-centered our variables when testing for potential multicollinearity issues. VIFs for the mean-centered variables were acceptable (all < 3.99), indicating that multicollinearity was unlikely to be an issue in our analysis.

Results

Main results. The parameter estimates for all model specifications are presented in Table 4. In model 4, we observed significant relationships between density and sales (β_1 = 0.095, p < .01), and between sales and the number of locations (β_2 = 0.275, p < .01), confirming prior research showing that higher densities lead to higher sales (Craig et al. 1984; Christaller 1933), and that more common brands had higher average sales. More importantly, there was a significant, negative interaction between brand commonness and density (β_3 = -0.034, p < .01). This indicates that at higher levels of brand commonness, the positive effect of higher population density on sales weakened, again supporting our prediction.

INSERT TABLE 4 HERE

INSERT TABLE 5 HERE

Robustness checks. We obtained consistent results when excluding all fixed effects (model 5, β_3 = -0.046, p < .01). Moreover, our results were robust to the inclusion of control variables capturing cannibalization and competition. We observed the same negative interaction effect when considering the effects of cannabilization and distribution (model 6, β_3 = -0.035, p < .01), the effects of competition and market concentration (model 7, β_3 = -0.030, p < .05), and when considering both these forces simultaneously (model 8, β_3 = -0.031, p < .05). Thus, controlling for cannabilization and competition, we continue to observe the predicted interaction effect of population density and brand commonness, suggesting that these are not plausible alternative explanations for our findings.

As brand distribution decisions may be subject to endogeneity, we also estimated model 6 using an instrumental variable approach similar to that of Gielens, et al. (2014). The model was estimated using two-step feasible GMM. For both the AREALOC and DIST1 variables, we employed the lagged average value of the variable for all competing brands (reducing the size of the panel), both at the county level and across the state as instruments. The Hansen J statistic (equivalent to a Sargan test in models with heteroskedasticity) indicated that the instruments were valid ($\chi^2(2) = 3.03$, $p > .22$), and the Kleibergen-Paap rk LM statistic suggested that the instruments were relevant ($\chi^2(3) = 12.53$, $p < .01$). Our results (model 9) are largely unchanged, save for a significant positive effect of the number of other locations for the brand in the same county. Most importantly, the interaction of density and brand commonness remains significant and negative ($\beta_3 = -0.037$, $p < .01$).

Overall, our results are consistent with the previously shown positive effect of population density on sales, but this effect was moderated by the commonness of the brand, in support of our predictions. These findings are unlikely to be due to competition or cannibalization of sales by other locations within the same area. We find that, after controlling for these factors, the negative interaction between population density and commonness remained significant, suggesting distinct explanations.

Addressing endogeneity of population density. We explored concerns about endogeneity of population density by considering exogenous factors that could affect it. Specifically, we examine an exogenous change in population density created by the population displacement from areas around the Gulf coast to multiple counties in Texas that occurred in the period following Hurricanes Katrina and Rita in August and September of 2005. Estimates of the number of people displaced range between 700,000 and 1.2 million people (Gabe, Falk, McCarty and Mason 2005), creating the "largest diaspora in U.S. history" (Ladd, Marszalek and Gill 2006). We employed a difference-in-differences approach, comparing the effect of brand commonness before and after the hurricanes in the counties identified by the Census Bureau where substantial immigration occurred to those counties that did not experience a major population increase. Similar to our prior results, we expected that we would observe a positive overall effect on sales due to the increase in population density, but that there would be a significant negative interaction effect with brand commonness in these counties.

We consider monthly alcohol sales data for 9,008 stores from 6,122 brands in 111 counties in Texas over a 24-month period from August 2004 to August 2006, one year before and one year after Hurricanes Katrina and Rita struck in August and September 2005. The Federal Emergency Management Agency identified 22 counties in Texas as "hurricane impacted" and eligible for assistance from the U.S. Federal Government, and the 12 counties within this set for which we had observations all experienced population increases according to special population estimates prepared by the U.S. Census following the hurricanes (Myers 2007; U.S. Census 2006). These 12 counties served as the treatment in our analysis. While we again employ county-level fixed effects that capture the heterogeneity among the counties, we note that the treatment counties are comparable in terms of population density (M = 338) to the untreated counties (M = 150), with 33% of the treated counties having densities of less 100 people per square mile. We average our data over quarters for clarity, though our results hold when analyzed at a monthly level.

We estimated sales using model (9). The independent variables included brand commonness, again operationalized by the log-transformed number of brand locations in the state, and a dummy-coded variable indicating the treatment effect (i.e., those counties in Texas identified by the Census Bureau as locations for immigration after the Hurricane events). We include fixed effects for location, brand, county and time, and employ robust standard errors clustered by county.

$$SALES_{it} = \beta_1\, TREATMENT_{kt} + \beta_2\, COM_{it} + \beta_3\, COM_{it} \cdot TREATMENT_{kt} + \mu_i + \mu_j + \mu_k + \mu_t + \varepsilon_{it} \qquad (9)$$

The results for this model are presented in table 6. We observed a positive effect of the treatment, indicating that sales increased in the impacted counties relative to other counties (β_1 = 0.020, $p < .05$), as we expected due to the increase in population density. However, this effect was qualified by a significant, negative interaction effect of the treatment and brand commonness, indicating that larger brands saw relatively lower boost in sales in the impacted counties after the hurricanes (β_3 = -0.015, $p < .01$). This suggests that, accordant with our expectations, more common brands experienced an effect consistent with the population penalty in areas that saw increases in population density due to displacement following these natural disasters.

INSERT TABLE 6 HERE

We also estimate a relative time model (10) to address the potential for differences in the trends of pre-treatment effects that would not be captured by brand and county-specific fixed effects, which present a threat to identification (Angrist and Pischke

2008). We employ a relative time approach (Autor 2003; Greenwood and Agarwal 2015; Wolfers 2006). This model uses a dichotomous indicator for affected counties, which was interacted with a series of time dummies representing the relative distance in quarters from the occurrence of the hurricanes in August-September 2005. These time dummies were also interacted with commonness, and their three-way interaction, where we expect to again observe a negative effect in the quarters following the event. Our dependent measure remains log-transformed quarterly sales.

The results of the analysis are presented in table 6. We observed significant positive effects in treated counties (relative to the untreated counties) in all four quarters following the event, consistent with an increase in population density leading to an increase in sales. More importantly, we observed a negative trend for the interaction of brand commonness and the treatment, with a marginal negative effect beginning in the second quarter following the event building to larger effects in subsequent quarters. Further, this analysis also provides strong evidence against potential differences in pre-treatment trends as the driver of our results. We do note that we observe two significant effects pre-treatment: a difference between treated and untreated counties at t_{-3}, and a relative effect of commonness at t_{-1}. However, neither of these effects appears part of a larger trend and could reasonably be expected in the estimation of the 26 parameters in the full model.

GENERAL DISCUSSION

Many marketing decisions are based on the financial benefits of operating in densely populated areas. For example, in retailing, population has long been known as a critical factor in the site selection process (Applebaum 1966; Christaller 1933; Craig, Ghosh and Lafferty 1984; Ghosh and Craig 1983; Goodchild 1984; Huff 1962; Stanley and Sewall 1976). Retailers often select sites using tools such as the buying power index, published by *Sales and Marketing Management* magazine, that combines population with other factors, such as income, to form an indicator of sales potential (2009 Survey of Buying Power). Population also plays an important role in sales strategies, including sales territory management (Spiro, et al. 2008) and market entry decisions (Young, et al. 1989). A survey of marketing directors indicated that market size is among the most important criteria in the selection of target markets (Simkin and Dibb 1998).

Yet, despite its importance, there is little research on the factors that affect the strength and direction of the population-sales performance relationship. Further, the extant research seems confident in suggesting that, other factors being equal, a larger population base leads to an increase in sales (e.g., Kumar and Karande 2000; Liu 1970; Pauler, et al. 2009). The findings presented in the current research demonstrate that this relationship is not always straightforward. Through five studies, combining experimental and empirical analysis, we show a novel effect of population density on brand preferences for identity relevant products. Across various product categories and countries, we show evidence for the population penalty, and that these effects are unlikely to be due to self-selection or other idiosyncratic differences between residents of urban and rural areas (studies 1 and 2) and are determined by a social distinctiveness process (studies 2 and 3). The findings also suggest that other explanations cannot explain the findings including distribution differences (studies 4 and 5), income differences (study 4), competition (studies 4 and 5), or cannibalization (study 5).

The results suggest that common, identity relevant brands should carefully consider the potential downsides of operating within densely populated areas. Beyond the well-known difficulties of densely populated locations, such as higher rents and labor costs, the population penalty explored here presents a potential cost that common brands should consider when locating in such areas. The current study is the first to investigate this phenomenon, integrating an analysis of marketing strategy at a broad level by observing actual sales, as well as considering the underlying influences of consumer psychology.

We present a clear linkage between consumer psychological reactions to population density, providing some insight into the process that generates this penalty. Though research has investigated the psychological effects of crowding on desires for uniqueness, this work has focused on smaller settings such as within rooms or stores (Xu, et al. 2012; Argo, et al. 2005). We extend research in this area by considering broader levels of analysis, including cities and regions, showing that the need for optimal distinctiveness can be driven by population density in a wide area, and contribute to a growing body of work investigating how crowding affects consumption-related behaviors (Andrews, et al. 2015).

Further, our work contributes to a growing body of work on the influences of population density on individuals' experiences (Sng, et al. 2017). Consistent with optimal distinctiveness predictions, desires to disaffiliate are affected by population density. Although, on the surface, such a process-related finding may seem less important to strategic influence, such knowledge could prove important in framing marketing communications to target individuals within densely populated locations, as well as potentially influencing branding decisions in such locations. For example, highlighting the uniqueness of a store's products in marketing messages may prove beneficial for chain retailers (e.g., a strategy followed by IKEA; Mochon, Norton and Ariely 2012), potentially offsetting the population penalty. Similarly, large chains may find a benefit in creating sub-brands in urban areas (Aaker 1994; Daley 2009; Milberg, Park and McCarthy 1997), in order to highlight their distinction from the common flagship brand. Starbucks employed this strategy with its Roy Street Coffee & Tea location, appearing unlike other Starbucks locations by replacing the typical Starbucks logo and green décor with a small coffeehouse atmosphere, rustic décor, and a different menu. We look forward to future research on this topic.

Limitations

We must emphasize that we do not recommend rejecting population as a criteria in marketing decisions, but instead hope to raise awareness of the variability of its relationship with sales. We urge marketers to consider a range of factors in conjunction with population such as demographics (e.g., age, income, and lifestyles), market conditions and strategic objectives.

Brand commonness may play a role in other marketing domains that rely on population as well. For instance, many advertising decisions are based on population sizes (e.g., TV, radio and billboards). It may be that the effectiveness of an advertisement in an area depends on both the population and the commonness of the brand being advertised. Without a study of advertising effectiveness, this is speculative, but we look forward to future research on this topic.

Additionally, brand commonness is only one moderator of the link between population and sales performance, and we expect that other factors moderate this relationship as well. Given the importance of this topic to marketers, future research is warranted. We believe approaching sales performance from a social identity lens offers a richer understanding of consumer behavior that we anticipate will help firms improve their performance.

Conclusions

When brands expand their reach into new markets, they need to consider the motives of consumers in the area and how they impact the perceptions of their products. Brands that are common should consider the potential consequences of the population penalty when forecasting their returns in a given geographical area. They may also take steps to attenuate the penalty's effects by ensuring that their products are viewed as unique in these markets.

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Appendix A. Manipulations used in study 1

Population density manipulation

[High population density]

The Crowded Life: Too Many, Too Much

By ERIC HAUSER FEBRUARY 15, 2017

Visitors across the United States are often confronted by increasingly large numbers of people who they encounter in public spaces. Nick Schnelle /The New York Times

[1]

PHOENIX, AZ — A few months ago, Bob Buckley and his family made their way to a local park on a sunny spring day. When they got there, they were shocked to find the park overrun with people. With no space to themselves, Bob's family couldn't help running into people— literally. They attempted to play soccer in a cramped field or find an open swing on a crowded playground, but in the end, there were just too many people. When asked about how he felt, Bob responded, "I felt very cramped and constrained. There were so many people, and no open space. It's like everywhere else these days—full of people."

Throughout the United States, people are becoming increasingly familiar with long lines,

[1] Photo courtesy of Raymond Castro.

big crowds, and giant traffic jams. There's a good reason for all this overcrowding. According to statistics released by the U.S. census this year, population densities are growing at an unprecedented rate. In almost every U.S. state, population densities are increasing rapidly. The population of Phoenix, Arizona, for example, was just over 100,000 in 1950. Now the Phoenix area is tipping the scales at over 4.3 million! And Phoenix isn't even the fastest growing American city. Three cities in Texas alone—Houston, Austin, and San Antonio are growing even more rapidly.

Ken Lithgau, the director of the City Planning Department for Raleigh, North Carolina — one of the fastest growing cities in the United States — said that the city's resources have been taxed to the limit trying to meet the needs of their new residents.

"We're constantly having to re-draft our proposals given the way the population is expanding. We're absolutely overwhelmed, and its not just housing. Its busier roads, packed public spaces, we have to think about all the ways in which these people will interact with the community. That means designing systems to handle large crowds everywhere people go in the city."

[Control]

Squirrel Explosion: Too Many, Too Much

By ERIC HAUSER FEBRUARY 15, 2017

Visitors across the United States are often confronted by increasingly large numbers of squirrels that they encounter in public spaces. Nick Schnelle / The New York Times

PHOENIX, AZ — A few months ago, Bob Buckley and his family made their way to a local park on a sunny spring day. When they got there, they were shocked to find the park overrun with squirrels. Within the limited space, Bob's family couldn't help running into the creatures. They attempted to play soccer in the field or find an open swing on the playground, but it was difficult to avoid them. When asked about how he felt, Bob responded, "I felt quite overwhelmed. There were so many of the critters. It seems like this is happening in other places too."

Throughout the United States, people are becoming increasingly familiar with a growing squirrel presence. According to statistics released by the National Parks Service this year, squirrel populations are growing at an unprecedented rate. In almost every U.S. state, populations have more than doubled in a space of 10 years. The population of ground squirrels in Flagstaff, Arizona, for example, was just over 8 million in 2000. Current estimates of the population are now over 20 million! And Arizona doesn't even have the fastest growing squirrel population. Colorado and California both have even higher growth rates.

Ken Lithgau, the director of the Parks and Recreation Department for Raleigh, North Carolina — a city with one of the fastest growing squirrel populations in the United States — said that the city's resources have been taxed to the limit trying to address the growth.

"We're constantly having to re-draft our proposals given the way the population is expanding. We're absolutely overwhelmed, and its not just in parks. They're in street easements and in backyards, we have to think about all the areas in which these animals may be found. That means coming up with a comprehensive management plan for everywhere these animals go in the city."

Appendix B. Manipulations used in study 2

Population density manipulation

[High population density] *Please think of the area were you currently live. Now imagine that in a very short time that lots of people living in your area moved away, so that the population shrank to only 1/4 of its current size.*

What would it be like to live there? How would you feel? Provide a brief example of what your day would be like.

[Low population density] *Please think of the area were you currently live. Now imagine that in a very short time that lots of people moved into your area, so that the population grew to 4 times its current size.*

What would it be like to live there? How would you feel? Provide a brief example of what your day would be like.

Motive prime manipulation

[Affiliation] *Even though many people have moved [away from][to] your area, please take a moment to think about a small, tightly knit social group that you belong to and feel a part of. You should feel you are this type of person and that you fit in with these people. This group should be quite specific, consisting of individuals who are very similar to one another.*

Please write down the name of this group.

[Disaffiliation] *Even though many people have moved [away][to] your area, please take a moment to think about a small, tightly knit social group still in the area that you do* ***not*** *belong to and do* ***not*** *feel a part of. You should feel you are not this type of person and that you do not fit in with these people. This group should be quite specific, consisting of individuals who are very similar to one another.*

Please write down the name of this group.

Appendix C. Manipulations used in study 3

Identity relevance manipulation

[High identity relevance] *Imagine that you need to buy clothing and there are four clothing stores in your area that you are considering. They offer similar selections and prices, but these brands have different number of locations worldwide. Some of these stores belong to large chains and others are small independent retailers.*

[Low identity relevance] *Imagine that you need to buy gas and there are four gas stations in your area that you are considering. They offer similar selections and prices, but these brands have different number of locations worldwide. Some of these stations belong to large chains and others are small independent retailers.*

Appendix D.

INSERT TABLE 7 HERE

Table 1. Purchase interest by area population density and affiliation prime (Study 2)

Interest in Shopping at Store with Many Locations

	Control	Disaffiliation Prime	Affiliation Prime	Overall Mean
Sparse Population	4.79^{1}	4.23^{2}	4.05	4.35
Dense Population	3.91^{1}	3.71^{2}	4.54	4.02
Overall Mean	4.35	3.98	4.28	4.19

Interest in Shopping at Store with Few Locations

	Control	Disaffiliation Prime	Affiliation Prime	Overall Mean
Sparse Population	4.18	4.70	4.81	4.57
Dense Population	4.07	4.66	4.36	4.38
Overall Mean	$4.13^{3,4}$	4.68^{3}	4.60^{4}	4.48

$^{1-4}$ indicate means different at $p < .05$.

Figure 1. Probability of shopping at common brands by population density (Study 3)

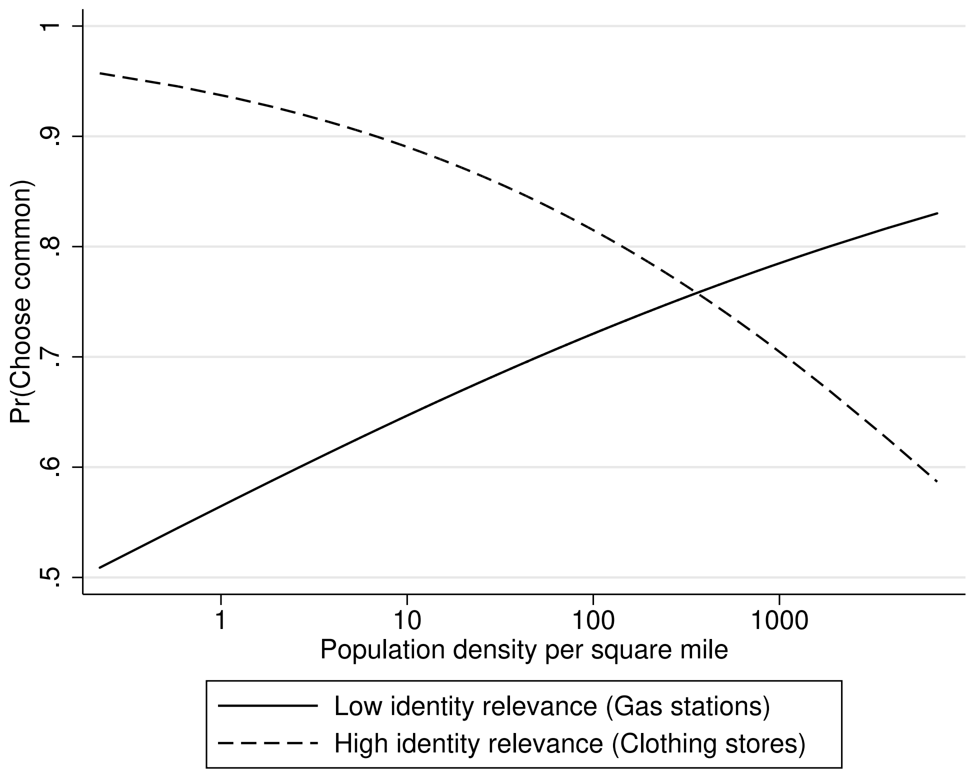

Table 2. Means and correlations for Study 4 Measures

	Variable	Description	Mean [1]	SD	Correlations 1	2	3	4	5	6
1.	SALES	Car Brand Sales	6,957.101	7,997.071	1.000					
2.	DEN	Population Density	755.981	1,426.005	−.063***	1.000				
3.	COM	Car Brand Commonness	1,022,564.131	1,003,319.078	.740***	.000	1.000			
4.	INCOME	Income	25,831.800	3,053.107	.071***	.907***	.005	1.000		
5.	PRICE	Average MSRP (€)	38,586.115	22,141.403	−.113***	.000	−.178***	.006	1.000	
6.	COMP	Region Competitor Sales	180,974.434	88,457.599	.350***	−.145***	−.059**	.170***	.022	1.000

$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .10$

[1] Untransformed values reported here.

Table 3. Estimates of UK regional car sales by brand, 2010-2014 (Study 4)

	(1)	(2)	(3)
DEN	2.543	3.255	.327***
	(1.674)	(2.737)	(.091)
COM	1.074***	1.026***	1.084***
	(.080)	(.081)	(.031)
DEN X COM	−.022***	−.015**	−.022***
	(.006)	(.006)	(.006)
INCOME		.044	
		(.049)	
PRICE		−.006***	
		(.001)	
COMP		−.895	
		(.852)	
Constant			−6.448***
			(.549)
Fixed Effects			
Location	Yes	Yes	No
Brand	Yes	Yes	No
Year	Yes	Yes	No
Observations	1,760	1,694	1,760
Overall R^2	.921	.917	
Within R^2	.055	.059	
Log pseudolikelihood			−1805.447

***$p < .01$, **$p < .05$, *$p < .10$

Robust standard errors displayed in parentheses (clustered on region).

Table 4. Means and correlations for Study 5 Measures

	Variable	Description	Mean[1]	SD	Correlations 1	2	3	4	5	6	7	8	9	10
1.	SALES	Alcohol Sales ($)	29,869.548	40,477.341	1.000									
2.	DEN	Population Density	1,175.214	835.737	.120***	1.000								
3.	COM	Bar/Rest. Brand Commonness [2]	8.117	20.593	−.020***	.002	1.000							
4.	AREALOC	Brand locations in county	1.854	2.883	−.030	.160***	−.647***	1.000						
5.	-DIST1	Distance to closest brand location (mi)	32.184	85.680	.028***	−.089***	−.026***	−.090***	1.000					
6.	-DIST10	Distance to 10th closest brand location (mi)	51.794	116.911	.065***	−.060***	.171***	.045***	.273***	1.000				
7.	COMP	Competitors in county	833.265	723.491	.093***	.663***	−.008***	.221***	−.096***	−.087***	1.000			
8.	HHI	County HHI	.029	.077	−.095***	−.262***	−.053***	−.102***	.031***	−.034***	−.265***	1.000		
9.	-CDIST1	Distance to closest competitor (mi)	.382	1.898	−.065***	−.110***	−.030***	−.031***	−.011***	−.035***	−.114***	.587***	1.000	
10.	-CDIST10	Distance to 10th closest competitor (mi)	2.190	6.495	−.105***	−.206***	−.032***	−.051***	.006***	−.036***	−.211***	.718***	.479***	1.000

***$p < .01$, **$p < .05$, *$p < .10$

[1] Untransformed values reported here.

[2] Averaged across all observations. Within brand, $M = 1.51$.

Table 5. Estimates of alcohol sales for Texas bars and restaurants, 2000-2011 (Study 5)

	(4)	(5)	(6)	(7)	(8)	(9)
DEN	.095***	.184**	.095***	.094***	.095***	.109***
	(.026)	(.005)	(.026)	(.026)	(.026)	(.023)
COM	.275***	.364***	.279***	.249***	.251***	.265***
	(.081)	(.023)	(.078)	(.081)	(.079)	(.072)
DEN X COM	−.034***	−.046***	−.035***	−.030**	−.031**	−.037***
	(.013)	.003	(.012)	(.013)	(.012)	(.011)
AREALOC			.003		.003	.034**
			(.016)		(.016)	(.014)
-DIST1			.060		.052	.091
			(.072)		(.072)	(.113)
-DIST10			−.041		−.046	−.084
			(.057)		(.056)	(.059)
COMP				−.159**	−.159**	
				(.077)	(.078)	
HHI				−.381	−.369	
				(.228)	(.226)	
-CDIST1				−.584	−.537	
				(5.231)	(5.263)	
-CDIST10				1.557	1.527	
				(1.538)	(1.551)	
Constant		8.281***				
		(.032)				
Fixed Effects						
Location	Yes	No	Yes	Yes	Yes	Yes
Brand	Yes	No	Yes	Yes	Yes	Yes
County	Yes	No	Yes	Yes	Yes	Yes
Year	Yes	No	Yes	Yes	Yes	Yes
Observations	101,779	101,779	101,779	101,779	101,779	81,264
Overall R^2	.938	.002	.938	.938	.938	.951
Within R^2	.001		.002	.002	.002	

$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .10$

Robust standard errors displayed in parentheses (clustered on county).

Table 6. Estimates of effects of Hurricanes Katrina and Rita on alcohol sales in affected counties in Texas, August 2004-August 2006 (Study 5)

	(9) Base Model			(10) Relative Time		
	TREATMENT	COM	TREATMENT X COM	TREATMENT	COM	TREATMENT X COM
Hurricanes Q_{-4}				.025	.004	$-.006$
				(.018)	(.004)	(.008)
Hurricanes Q_{-3}				$.053^{**}$	.007	$-.008$
				(.022)	(.006)	(.008)
Hurricanes Q_{-2}				$-.003$	.008	.001
				(.011)	(.005)	(.005)
Hurricanes Q_{-1}				.030	$.013^{***}$	$-.004$
				(.020)	(.003)	(.005)
Baseline	$.034^{***}$	.023	$-.014^{***}$	Excluded	.003	$-.026$
	(.009)	(.014)	(.002)		(.012)	.021
Hurricanes Q_{+1}				$.086^{***}$	$-.004$	$-.010$
				(.017)	(.007)	(.008)
Hurricanes Q_{+2}				$.046^{***}$	$-.002$	$-.010^{*}$
				(.017)	(.005)	(.005)
Hurricanes Q_{+3}				$.057^{**}$	$.009^{**}$	$-.014^{**}$
				(.022)	(.004)	(.006)
Hurricanes Q_{+4}				$.032^{***}$	$-.005$	$-.013^{***}$
				(.010)	(.003)	(.004)
Fixed Effects						
Location		Yes			Yes	
Brand		Yes			Yes	
County		Yes			Yes	
Quarter		Yes			Yes	
Observations		66,165			66,165	
Overall R^2		.956			.956	
Within R^2		.001			.002	

$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .10$

Robust standard errors displayed in parentheses (clustered on county).

Table 7. Summary of Robustness Tests for Alternative Explanations

Alternative Explanation	Test	Study	Finding
Competition rather than population density is driving population penalty	Include controls for competitive sales, number of competitors and spatial competition	4, 5	No changes in results when accounting for competition
Negative effect of cannibalization is more likely in densely populated areas	Include controls for distribution itensity	5	No changes in results when accounting for cannibalization
Higher income levels in densely populated areas allow purchase of more expensive, less common brands	Include controls for regional income and brand sale prices	4	No changes in results when accounting for income and sale prices
Less common brands do better in big cities because there is a critical mass to justify distribution	Examine if results hold among brands distributed in all regions	4	All brands distributed in all regions and results hold
Self-selection – individuals with higher needs for distinctiveness locate in densely populated areas	Experimentally manipulate feelings of population density	1, 2	Manipulated population density affects interest in common brands
	Examine natural quasi-experiment with exogenous change in population density	5	Lower sales observed for common brands in affected areas