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Positional Goods and the Social Rank Hypothesis: Income Inequality Affects Online Chatter about High- and Low-Status Brands on Twitter

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According to a social rank hypothesis, consumers who live in regions with higher income inequality will show greater interest in, and attention toward, positional goods and high-status brands that serve a social signaling role. We analyze millions of posts on the microblogging platform Twitter for mentions of high- and low-status brands. We find that luxury brands such as “Louis Vuitton” and “Rolex” are more frequently mentioned in tweets originating from US states, counties, and major metropolitan areas with higher levels of income inequality. In contrast, mentions of everyday brands such as “Walmart” or “Kmart” are more frequent in regions with a more equal distribution of income. Using sentiment analysis, we find higher valence (positivity) and arousal (excitement) for tweets that both mention high-status brands and originate from regions with high levels of income inequality. These results corroborate the social rank hypothesis, showing that more psychological resources are allocated to positional consumption when the income gap between the rich and the poor is larger.

Keywords Income inequality; Consumerism; Positional consumption; Twitter; Social rank hypothesis; Sentiment analysis; Status goods

In 2013, spending on pleasure aircraft was the fastest-growing category of consumer expenditure in the United States, and sellers of luxury goods have been thriving (e.g., Schwartz, 2014). Increasing disparities between the incomes of the richest members of society and those of the middle and poorest segments reflect growing income inequality in developed Anglophone countries in recent decades (e.g., Stiglitz, 2012). But how does income inequality affect consumers’ attention toward positional goods and high-status brands? Positional goods are those that confer high social status on those who possess them. A crucial feature is their scarcity, which is often achieved through high prices (Hirsch, 1977). Here, motivated by the idea that societal income inequality is associated with a greater focus on social comparison and status as revealed by the possession of positional goods, we develop and test the hypothesis that consumers’ levels of social media activity relating to high-status brands, but not low-status brands, will be greater when income inequality is high.

The Social Rank Hypothesis

Income and wealth inequality is now recognized as a potential source of numerous socio-economic problems in well-developed countries (Kawachi, Kennedy, Lochner, & Prothrow-Stith, 1997; Lynch et al., 2004; OECD, 2011; Pickett & Wilkinson, 2010). While social science and epidemiological research have led the way in identifying associations between income inequality and various indices of societal ill-being, there is a striking lack

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of theory concerning the precise mechanisms that might give rise to such effects at the level of the individual. In particular, the question of how a rational agent might behave differently when living in an unequal society has not been sufficiently examined.

Which psychological mechanisms explain the link between income inequality, status-seeking behavior on the part of consumers, and the loss of societal well-being? Here, we develop and test the social rank hypothesis (Daly, Boyce, & Wood, 2015; Walasek & Brown, 2015, 2016), according to which income inequality directly influences consumers' consumption preferences. The social rank hypothesis is motivated by the fact that it is relative income, not just absolute income, that is associated with subjective well-being (Clark, Kristensen, & Westergård-Nielsen, 2009; Clark & Oswald, 1996; Luttmer, 2005). More specifically, recent findings suggest that individual well-being stems from the social rank that income confers as well as, or instead of, from income per se (Boyce, Brown, & Moore, 2010). According to the social rank hypothesis, income, along with other fitness markers such as physical attractiveness, trustworthiness, social ability, etc., acts as an indicator of social status. To succeed, members of a society must be able to judge the position of themselves and others in the social hierarchy by accurately identifying their relative ranked position in the income distribution as well as by evaluating other characteristics such as attractiveness and trustworthiness.

Why might a concern with income-related social rank lead to greater attention to positional goods under conditions of high-income inequality? According to the social rank hypothesis, part of the explanation lies in the fact that a person's income rank can be more accurately identified (from visible cues such as ownership of positional goods) when income inequality is high. More specifically, when estimating an individual's social rank in an income or wealth distribution, people must rely on error-prone signals about how rich and poor others are. The logic is illustrated in Figure 1 (see also Brown, Boyce, & Wood, 2015), where the two panels show cumulative income distributions in a relatively equal (GINI = 0.28; top panel) and a relatively unequal (GINI = 0.48; bottom panel) society. As indicated by the dashed lines, a constant error on the horizontal (income) axis translates into much larger error on the vertical axis (relative rank of income) when the income distribution is less dispersed (top panel).

If income-related cues are more reliable indicators of income-related social rank in more unequal societies, rational agents should pay relatively more attention to such cues in such societies (and correspondingly will devote relatively less attention to other dimensions such as trustworthiness). In other words, people can be expected to attend more to the characteristics of other people that most accurately predict their social status. Here, we propose that positional goods may serve such a role (cf. Saad, 2011), and hence that individuals with a greater concern for such status are likely to devote more cognitive and other resources to conspicuous consumption and status-conferring positional goods. It is this prediction that the present paper tests.

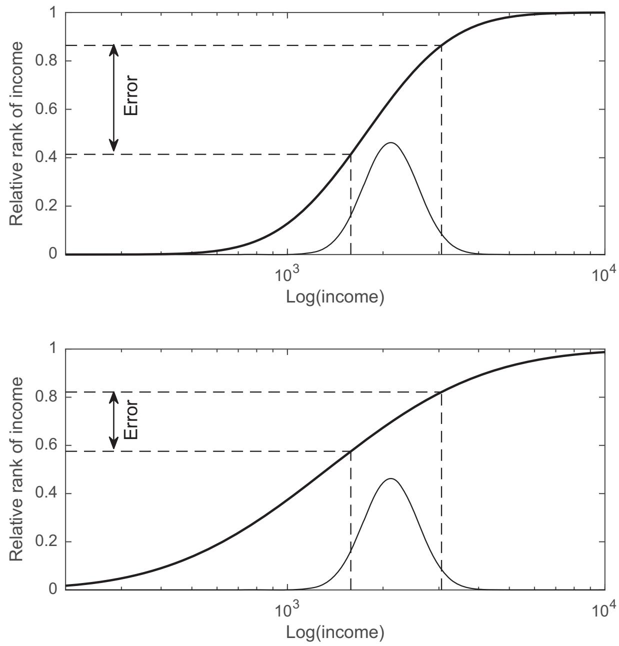

Figure 1. Hypothetical cumulative income distributions in a relatively equal (GINI = 0.28; top panel) and relatively unequal (GINI = 0.48; bottom panel) society. As indicated by the dashed lines, a constant error on the horizontal (income) axis translates into much larger error on the vertical axis (relative rank of income) when the income distribution is less dispersed (top panel).

Inequality and Consumption

How might a greater concern with status-related interpersonal comparisons be reflected in consumers' everyday behavior? Existing evidence suggests that income inequality leads to a greater readiness to go into debt and an increase in spending on visible goods. Thus, inequality is positively associated with people's tendency to spend a higher proportion of their disposable income

(Alvarez-Cuadrado & Attar, 2012; Cynamon & Fazzari, 2013; Heffetz, 2011), and relatedly, with a higher chance of entering debt and declaring bankruptcy (Perugini, Jens, & Collie, 2015). Several recent economic models maintain that the higher level of consumer borrowing in more unequal societies is driven by an increase in conspicuous consumption (e.g., Christen & Morgan, 2005; Ryoo & Kim, 2014). Consistent with the social signaling account, such spending behavior appears to be motivated by social comparison, whereby people attempt to appear better-off than other members of their social circle (e.g., their neighbors, co-workers; Heffetz, 2011).

Data on people's spending and borrowing therefore shed light on the relationship between income inequality and positional consumption, but such data are limited as a measure of interest and attention because an individual's ability to spend and borrow is ultimately constrained by their economic circumstances. A full understanding of the psychological underpinnings of attention to status requires data on people's shared interest in, and attitudes toward, positional consumption. Evidence for a relationship between interest in luxury brands and income inequality was found by Walasek and Brown (2015), who examined Google searching behavior and found that in US states with relatively high GINI coefficients (i.e., higher-income inequality), a higher relative proportion of people's searches related to luxury brands of jewelry, clothes, and perfumes. Similar results appear at a cross-national level (Walasek & Brown, 2016). These results reveal people's interest in status-related goods in a way that is not possible using real spending data (because spending is subject to budgetary constraints). A major limitation of such studies, however, is that searches on Google are essentially private and hence offer only an indirect test of the social rank hypothesis. The present paper offers a more direct test, using social media.

Positional Consumption and Twitter

Here, we provide a novel test of the social rank hypothesis by studying how social media chatter about low- and high-status brands varies as a function of regional levels of income inequality. More specifically, we collect millions of geo-located posts (tweets) from the popular microblogging platform, Twitter. By analyzing tweets' content, we can determine the frequency with which positional goods are mentioned and how such frequency varies as a function of tweeters' geographical locations.

Using tweets as an index of consumers' social signaling behavior extends previous efforts in a number of important ways. Twitter is inherently social, with most posts being available for public viewing. Tweeting therefore provides a channel for expressing interest in and attitudes toward specific products and brands. A decision to retweet, for example, can be seen as an explicit signal of the users' shared interests, values, or attitudes. Unlike expenditure-based measures, socially visible online activity is only weakly limited by affordability constraints, at least in wealthy nations where the majority of the population have ready access to the Internet. Thus, even people who cannot afford high-status goods may nevertheless devote time to tweeting about, or discussing, such goods.

Moreover, the content of individual tweets can be used to test the predictions of the social rank hypothesis more precisely than is possible with Google searches. For example, previous tests using Google searches were limited to country-level and state-level analysis. Many tweets, however, contain information about the coordinates (latitude and longitude) from which the tweet originated. This allows us to test the relationship between the frequency of brand-related tweeting and income inequality with finer geographical resolution (i.e., counties and metropolitan areas in the United States). The content of tweets can also be used to test novel predictions about the manner in which people express their interest in status competition and positional goods. First of all, Google Correlate analysis only yields a small number of brands that are correlated with income inequality (see Walasek & Brown, 2015 for details), making extensive analysis impossible. In contrast, we are unconstrained in the number of brands that we can screen Twitter activity for. Second, it is possible to compute arousal and sentiment scores for each individual tweet, which is not possible with Google Correlate. These scores allow us to quantify the positivity and emotional intensity with which people talk about different brands ("sentiment analysis").

Predictions

Our primary prediction is that people living in more unequal regions will spend more of their time and resources (here, posting online) about luxury (positional) brands. What does the social rank hypothesis predict for the frequency of mentions of low-status brands? Status considerations, as determined by consumption patterns, are hypothesized to be particularly important in regions with high inequality. Thus, being associated with cheap and common brands should be regarded as a negative signal of one's position in the society. We therefore predict that we should find less online chatter about cheap and low-status brands in regions with greater income inequality.

Further predictions concern the emotional content of the language used when talking about high- and low-status brands. The social rank hypothesis does not in itself make a clear prediction about the direction of sentiment effects. However, we propose a subsidiary *positional anxiety hypothesis*. Under this hypothesis, individuals' thoughts about their rank position within an income/wealth distribution will produce status anxiety. Hence, greater levels of cognizing about positional goods will be associated with negative affect (cf. Layte & Whelan, 2014; Pickett & Wilkinson, 2010). We will use sentiment analysis to test this subsidiary hypothesis.

Method

Brand Listing

First, we used a survey conducted on Amazon Mechanical Turk to obtain a representative list of consumer brands (Walasek & Brown, 2016). Using a between-subjects design, Walasek and Brown asked 275 respondents to list up to 10 consumer brands that are associated with high (n = 78 participants) or low (n = 70 participants) social status. For unrelated purposes, a third of our sample listed brands without any reference to social status. The exact instructions in the high (low) status condition read:

> In the following task, we would like you to list ten brands. We are interested in **high (low) status** brands/makes/labels of any consumer products that you can think of. High (low) status refers to brands that are associated with high (low) income and wealth.

Each participant was rewarded with \$0.50 for their time. Our analysis proceeded as follows. First, we identified and corrected spelling errors (e.g., "Louis Vuitton" and "Louis Vuiton"). From the two resulting lists, we picked the top 10 most frequently mentioned brands (the complete list of brands mentioned at least twice is included in Table S1). The high-status brands were "Gucci," "Mercedes," "Louis Vuitton," "Rolex," "BMW," "Chanel," "Apple," "Prada," "Armani," and "Versace." The low-status brands were "Walmart," "Great Value," "Kmart," "McDonalds," "Aldi," "Burger King," "Dollar General," "KIA," "Ford," and "Equate."

Twitter Samples

We collected two samples of geo-located tweets from the United States. Our first sample was based on a streaming session run between 17th and 20th of October 2014. Our second sample was collected between 10th October and 14th of November 2016. In the pre-processing of each sample, we included retweets (tweets that are copied and reposted), and excluded tweets that contained only links. We also removed non-English characters, white spaces, references to other users (@username), and numbers (e.g., 123) from every tweet. In determining the location of each tweet, we crossed each tweet's latitude and longitude of origin with the cartographic boundaries of US states, counties, and metropolitan areas. We outline this process in our Methodological Details Appendix. Our geo-location procedure left us with 5,529,126; 5,346,871, and 5,226,361 tweets in the first sample (geo-located at state, county, and metro level, respectively). Totals in the second sample were 35,476,770; 21,762,266, and 29,665,317.

We screened each of the remaining tweets for mentions of high- and low-status brands. We searched for exact matches, thus avoiding situations in which a brand name may be a part of another word (e.g., *ford* and *afford*). Due to missing data, we excluded Puerto Rico and Washington DC from the analysis.

Variables

We obtained a number of socio-economic indicators at the level of individual states, counties, and metropolitan areas from the US Census Bureau. These are based on the 5-year estimates from the 2014 American Community Survey. We used the GINI coefficient as our measure of income inequality; this measure captures dispersion of income with 0 representing perfect equality (all income is shared equally) and 1 representing the highest possible inequality (all income is concentrated in the hands of one individual). From the US Census Bureau data, we obtained 5-year estimates for mean household income, total population, percent foreign-born residents, proportion of the population earning over \$100k, proportion of the population earning over \$200k, and the percentage of the population living in urban areas (U.S. Census Bureau, 2015a,b,c,d,e). These variables were used as covariates in our analysis.

Results and Discussion

In a series of Poisson regressions, we tested whether the number of mentions of high- and low-status brands on Twitter is associated with regional level of income inequality. We begin by summarizing regressions predicting mentions of the high-status brands, for each level of geography (state, county, and metro), with the inclusion of socio-economic covariates. Although we cannot control for individual income, we use regional indices of household income as covariates in our models. Table 1 shows model summaries for both samples of tweets. We present results from each sample separately to demonstrate robustness and because of between-sample differences in geolocation quality (see Appendix S1).

As expected, we find a positive association between income and the number of mentions of luxury brands on Twitter. Crucially, we find the predicted positive effect of GINI. The findings are consistent with the social rank hypothesis, showing that the higher the income inequality in a given region, the larger is the number of mentions of high status, luxury brands in tweets from that region. We observe this association at the level of US states (Sample 1: $\beta = 1.36$, CI [0.05; 2.66]; Sample 2: $\beta = 2.71$, CI [2.04; 3.37]), counties (Sample 1: $\beta = 2.10$, CI [1.62; 2.59]; Sample 2: $\beta = 3.05$, CI [2.75; 3.36]), and metropolitan areas (Sample 1: $\beta = 1.41$, CI [0.40; 2.42]; Sample 2: $\beta = 0.42$, CI [−0.10; 0.94]), with statistical significance for all samples except the second metropolitan area sample.

We also conducted a regression without covariates, the results of which are reported in Table M1 in the Appendix S1. The pattern of findings was largely identical although the key coefficients were generally larger in the absence of controls. In Table 2 we report additional analyses with mentions of low-status brands as our dependent variable.

At all spatial levels of analysis, we find a negative association such that mentions of low-status brands (e.g., "Walmart," "Kmart") occur less frequently in regions with high-income inequality. We observe this association significantly at the level of

Table 1
Results of Full Regression Models for the Analysis of the Mentions of High-Status Brands on Twitter

	Sample 1			Sample 2		
	Coef.	95% CIs	*p*	Coef.	95% CIs	*p*
Level: State						
Intercept	−16.41	[−18.59; −14.24]		−11.37	[−12.41; −10.34]	
GINI	1.36	[0.05; 2.66]	.041	2.71	[2.04; 3.37]	<.001
Perc. Foreign	0.01	[0.002; 0.02]	.007	0.008	[0.005; 0.01]	<.001
Population	-1.98×10^{-10}	[-8.71×10^{-9}; 8.32×10^{-9}]	.964	-1.35×10^{-8}	[-1.74×10^{-8}; -9.54×10^{-9}]	<.001
Log Income	0.90	[0.71; 1.09]	<.001	0.33	[0.24; 0.42]	<.001
Perc. Urban	−0.01	−0.01; −0.004	<.001	−0.0005	[−0.002; 0.001]	.573
		χ^2 (5) = 276.53, p < .001			χ^2 (5) = 530.47, p < .001	
Level: County						
Intercept	−15.42	[−16.36; −14.48]		−13.73	[−14.26; −13.20]	
GINI	2.10	[1.62; 2.59]	<.001	3.05	[2.75; 3.36]	<.001
Perc. Foreign	0.01	[0.01; 0.01]	<.001	0.002	[0.001; 0.003]	<.001
Population	-1.46×10^{-7}	[1.78×10^{-7}; -1.14×10^{-7}]	<.001	-1.54×10^{-8}	[-3.21×10^{-8}; 1.26×10^{-9}]	.070
Log Income	0.74	[0.66; 0.82]	<.001	0.53	[0.48; 0.58]	<.001
Perc. Urban	0.001	[−0.0003; 0.002]	.132	−0.003	[−0.004; −0.002]	<.001
		χ^2 (5) = 774.74, p < .001			χ^2 (5) = 1,852.98, p < .001	
Level: Metro						
Intercept	−17.01	[−18.48; −15.54]		−11.33	[−12.14; −10.52]	
GINI	1.41	[0.40; 2.42]	.006	0.42	[−0.10; 0.94]	.116
Perc. Foreign	0.006	[0.003; 0.009]	<.001	0.004	[0.003; 0.006]	<.001
Population	-3.15×10^{-8}	[-4.54×10^{-8}; -1.76×10^{-8}]	<.001	1.79×10^{-8}	[9.98×10^{-9}; 2.57×10^{-8}]	<.001
Log Income	0.91	[0.79; 1.03]	<.001	0.41	[0.35; 48]	<.001
		χ^2 (4) = 493.13, p < .001			χ^2 (4) = 946.94, p < .001	

Table 2
Results of Full Regression Models for the Analysis of the Mentions of Low-Status Brands on Twitter

	Sample 1			Sample 2		
	Coef.	95% CIs	p	Coef.	95% CIs	p
Level: State						
Intercept	−0.64	[−4.81; 3.53]		2.88	[0.69; 5.07]	
GINI	−4.03	[−6.61; −1.45]	.002	−0.14	[−1.51; 1.23]	.843
Perc. Foreign	−0.009	[−0.02; 0.002]	.117	−0.011	[−0.02; −0.01]	<.001
Population	-3.28×10^{-9}	$[-1.92 \times 10^{-8}; 1.26 \times 10^{-8}]$	.686	2.88×10^{-9}	$[-5.05 \times 10^{-9}; 1.08 \times 10^{-8}]$	.477
Log Income	−0.39	[−0.75; −0.03]	.034	−0.93	[−1.12; −0.74]	<.001
Perc. Urban	−0.003	[−0.009; 0.002]	.252	−0.001	[−0.004; 0.002]	.625
		χ^2 (5) = 145.05, p < .001			χ^2(5) = 627.01, p < .001	
Level: County						
Intercept	−1.81	[−3.93; 0.31]		4.14	[2.80; 5.48]	
GINI	−3.80	[−4.85; −2.75]	<.001	−3.98	[−4.68; −3.28]	<.001
Perc. Foreign	−0.01	[−0.02; −01]	<.001	−0.009	[−0.01; −0.006]	<.001
Population	-3.03×10^{-8}	$[-1.05 \times 10^{-7}; 4.42 \times 10^{-8}]$	.426	5.33×10^{-8}	$[1.17 \times 10^{-8}; 9.49 \times 10^{-8}]$	.012
Log Income	−0.32	[−0.50; −0.14]	<.001	−0.89	[−1.003; −0.78]	<.001
Perc. Urban	0.002	[−0.0001; 0.004]	.064	0.004	[0.003; 0.005]	<.001
		χ^2 (5) = 298.24, p < .001			χ^2 (5) = 1,113.01, p < .001	
Level: Metro						
Intercept	2.13	[−0.83; 5.09]		8.10	[6.45; 9.76]	
GINI	−3.64	[−5.47; −1.81]	<.001	−2.11	[−3.06; −1.16]	<.001
Perc. Foreign	−0.01	[−0.02; −0.01]	<.001	−0.005	[−0.01; −0.002]	<.001
Population	6.88×10^{-9}	$[-2.67 \times 10^{-8}; 4.04 \times 10^{-8}]$	.688	6.80×10^{-9}	$[1.29 \times 10^{-8}; 2.65 \times 10^{-8}]$	.499
Log Income	−0.68	[−0.92; −0.44]	<.001	−1.32	[−1.46; −1.19]	<.001
		χ^2 (4) = 217.37, p < .001			χ^2 (4) = 997.91, p < .001	

US states for one of the samples (Sample 1: β = −4.03, CI [−6.61; −1.45]; Sample 2: β = −0.14, CI [−1.51; 1.23]), and for all other geographies and samples, including counties (Sample 1: β = −3.80, CI [−4.85; −2.75]; Sample 2: β = −3.98, CI [−4.68; −3.28]), and metropolitan areas (Sample 1: β = −3.64, CI [−5.47; −1.81]; Sample 2: β = −2.11, CI [−3.06; −1.16]). These findings are consistent with the social rank hypothesis as they show that signals associated with low wealth and income are less prevalent in regions where such signals are generally more accurate in determining one's social rank.

We again conducted a regression without covariates, the results of which are reported in Table M1 in Appendix S1. The pattern of findings was largely identical. For robustness, we replicated all of the analyses reported in Tables 1 and 2, but using lists only of brands identified by at least 10 participants in our survey as our dependent variable. The results, which are largely consistent with the findings reported above, are summarized in Tables M2 and M3 in Appendix S1.

In sum, our results support predictions of the social rank hypothesis even after controlling for a range of socio-economic factors, including aggregate levels of household income. However, as Walasek and Brown (2015) noted, interest in status goods may reflect a non-linear effect of income on the interest in high-status goods. In other words, simply controlling for mean income does not exclude the possibility that the positive association between inequality and mentions of high-status brands is driven by the richest members of the population. We therefore conducted further analyses where we replaced the mean income of a region with the proportion of the population of the region earning above 100k a year. All regression tables are reported in the Methodological Details Appendix but, in summary, our findings are largely consistent with the results reported above. In further analyses (unreported here), we find the same pattern of results when an income threshold of 200k is used. These additional analyses are important as they show that it is not simply the case that only richer areas show stronger interest in expensive and luxurious brands.

To further explore people's attitudes toward high- and low-status brands, we calculated sentiment and arousal scores for all tweets in our two samples. We computed both scores using the dataset from Brysbaert, Warriner, and Kuperman (2014), which contains word-valence ratings for 13,915 English words. Each tweet was scored based on the average valence and arousal of its component words, with scores ranging from 1 to 9 and higher values representing more positive emotions or higher arousal associated with the entire tweet. To test our subsidiary positional status hypothesis, we examined whether tweets that mentioned high-status brands more often than low-status brands in regions of high inequality were associated with changed valence and/or arousal. We first calculated the difference between the number of mentions of high-status brands and the number of mentions of low-status brands within each tweet. In our regression model, we used this difference score (*S*-diff in Table 3), the GINI coefficient, and critically, their interaction as predictors of both valence and arousal. We conducted these analyses for both samples of tweets and for all levels of geographical division. Tables 3 and 4 summarize results for the measure of tweets' valence and arousal, respectively.

In all models, we found a significant and positive interaction between GINI and the difference score. Specifically, tweets in which high-status brands were mentioned more often than low-status brands displayed more positive sentiment and higher arousal where income inequality is high. For valence, the coefficients on the key interaction were positive for US states (Sample 1: $\beta = 28.22$, CI [15.84; 40.60]; Sample 2: $\beta = 17.72$, CI [11.00; 24.12]), counties (Sample 1: $\beta = 12.51$, CI [7.29; 17.72]; Sample 2: $\beta = 5.72$, CI [2.32; 9.11]), and metropolitan areas (Sample 1: $\beta = 18.37$, CI [9.48; 27.25]; Sample 2: $\beta = 8.48$, CI [3.46; 13.50]). For arousal, the coefficients on the key interaction were positive for US states (Sample 1: $\beta = 20.24$, CI [11.51; 28.98]; Sample 2: $\beta = 12.62$, CI [7.89; 17.36]), counties (Sample 1: $\beta = 8.73$, CI [5.05; 12.40]; Sample 2: $\beta = 4.07$, CI [1.70; 6.44]), and metropolitan areas (Sample 1: $\beta = 12.73$, CI [6.47; 19.00]; Sample 2: $\beta = 6.89$, CI [3.36; 10.42]). We interpret this as evidence against the positional anxiety hypothesis, as the higher frequency of mentions of high-status brands when income inequality is high was not associated with negative sentiment. Moreover, the results regarding arousal are consistent with the suggestion that greater psychological resources are allocated to positional goods in regions with high inequality.

General Discussion

Understanding how income inequality influences consumer behavior requires a psychological model to explain how individuals respond, in terms of their attitudes, beliefs, and preferences, to the

Table 3
Valence Analysis for Each Subset of the Data

	Sample 1			Sample 2		
	Coef.	95% CIs	*p*	Coef.	95% CIs	*p*
Level: State						
Intercept	21.59	[21.26; 21.93]		28.58	[28.43; 28.73]	
S-diff	−8.35	[−14.20; −2.50]	.005	−3.26	[−6.44; −0.09]	.044
$\text{GINI}_{\text{state}}$	−12.76	[−13.47; −12.05]	<.001	−25.08	[−25.40; −24.76]	<.001
S-diff × $\text{GINI}_{\text{state}}$	28.22	[15.84; 40.60]	<.001	17.72	[11.00; 24.12]	<.001
		$F(3,5529122) = 1{,}145$, $p < .001$			$F(3,35476766) = 1{,}0967.48$, $p < .001$	
Level: County						
Intercept	13.91	[13.77; 14.06]		16.05	[15.96; 16.13]	
S-diff	−1.04	[−3.48; 1.40]	.404	2.18	[0.59; 3.77]	.007
$\text{GINI}_{\text{county}}$	3.48	[3.17; 3.79]	<.001	3.32	[3.14; 3.50]	<.001
S-diff × $\text{GINI}_{\text{county}}$	12.51	[7.29; 17.72]	<.001	5.72	[2.32; 9.11]	.001
		$F(3,5346867) = 842.43$, $p < .001$			$F(3,21762262) = 2{,}220.26$, $p < .001$	
Level: Metro						
Intercept	17.60	[17.36; 17.83]		23.61	[23.50; 23.72]	
S-diff	−3.65	[−7.80; 0.50]	.085	0.95	[−1.39; 3.30]	.426
$\text{GINI}_{\text{metro}}$	−4.25	[−4.76; −3.75]	<.001	−14.36	[−14.60; −14.12]	<.001
S-diff × $\text{GINI}_{\text{metro}}$	18.37	[9.48; 27.25]	<.001	8.48	[3.46; 13.50]	.001
		$F(3,5226357) = 785.03$, $p < .001$			$F(3,29665313) = 7{,}057.32$, $p < .001$	

Table 4
Arousal Analysis for Each Subset of the Data

	Sample 1			Sample 2		
	Coef.	95% CIs	*p*	Coef.	95% CIs	*p*
Level: State						
Intercept	15.52	[15.28; 15.75]		19.67	[19.56; 19.78]	
S-diff	−6.75	[−10.88; −2.63]	.001	−3.03	[−5.27; −0.80]	.008
$\text{GINI}_{\text{state}}$	−9.23	[−9.73; −8.73]	<.001	−16.33	[−16.55; −16.10]	<.001
S-diff × $\text{GINI}_{\text{state}}$	20.24	[11.51; 28.98]	<.001	12.62	[7.89; 17.36]	<.001
		$F(3,5529122) = 903.98$, $p < .001$			$F(3,35476766) = 8{,}784.07$, $p < .001$	
Level: County						
Intercept	10.10	[9.10; 10.20]		11.73	[11.67; 11.78]	
S-diff	−1.38	[−3.10; 0.34]	.115	0.83	[−0.29; 1.94]	.145
$\text{GINI}_{\text{county}}$	2.22	[1.10; 2.44]	<.001	1.61	[1.49; 1.74]	<.001
S-diff × $\text{GINI}_{\text{county}}$	8.73	[5.05; 12.40]	<.001	4.07	[1.70; 6.44]	.001
		$F(3,5346867) = 565.59$, $p < .001$			$F(3,21762262) = 1{,}363.04$, $p < .001$	
Level: Metro						
Intercept	12.66	[12.49; 12.82]		16.55	[16.47; 16.63]	
S-diff	−3.17	[−6.10; −0.25]	.034	−0.42	[−2.07; 1.22]	.614
$\text{GINI}_{\text{metro}}$	−3.14	[−3.50; −2.79]	<.001	−9.64	[−9.81; −9.47]	<.001
S-diff × $\text{GINI}_{\text{metro}}$	12.73	[6.47; 19.00]	<.001	6.89	[3.36; 10.42]	<.001
		$F(3,5226357) = 541.82$, $p < .001$			$F(3,29665313) = 5{,}819.81$, $p < .001$	

widening disparities between the rich and the poor in their society. According to the social rank hypothesis, people care about their rank position and actively choose how to best signal their status. In our model, if the local income dispersion is high, status based on one's wealth and income becomes a better signal of one's societal standing (see Figure 1). It therefore follows that people should spend more of their resources-seeking positional goods, as these goods signal high income when inequality is high.

In the present paper, we tested these predictions using large volumes of unsolicited online communication on Twitter. Specifically, we showed that people tweet more about high-status brands such as "Louis Vuitton" or "Chanel" in US regions where income inequality is higher. Mentions of low-status brands, such as "Walmart" or "McDonalds" were in contrast less frequent in regions with larger disparities in the income distribution. These results were shown in two independent samples containing millions of tweets, and across three levels of geographical division in the US: state, county, metropolitan areas. We showed that these results are robust to the inclusion of controls and cannot be explained by regional differences in the absolute level of income (both the mean income and the earnings of the richest) or a variety of other socioeconomic variables. These results complement and extend to the domain of social media previous research on Google searches (Walasek & Brown, 2015, 2016) which showed that people's interest in positional consumption is positively correlated with income inequality.

We note a possible confound between the income inequality within a region and the availability of positional goods within that region. Our account assumes that income inequality leads to greater concern with positional goods, and that it is this concern that leads to a higher frequency of brand-related tweeting. The greater consumer interest may of course also lead (through the operation of normal market forces) to the increased availability of outlets selling positional goods, as supply rises to meet demand. This availability may lead to greater likelihood of tweeting. However, full resolution of the complex dynamic interplay between the relevant causal factors will require longitudinal data or intervention studies of a type not yet available.

Our analysis of the language used on Twitter also offers new insights about people's attitudes toward different brands. We found that both positivity and arousal are high when tweets both mention high-status brands and originate from a region with a high GINI coefficient. In the context of the social rank hypothesis, it appears that people's communications about markers of high status are associated with stronger and more positive emotional responses.

Appendix

Table A1
High and low status brands identified by at least two participants of the online survey

High status brands		Low status brands	
Brand name	Frequency	Brand name	Frequency
GUCCI	42	WALMART	33
MERCEDES	39	GREAT VALUE	23
LOUIS VUITTON	32	KMART	16
ROLEX	32	MCDONALDS	14
BMW	31	ALDI	10
CHANEL	28	BURGER KING	10
APPLE	26	DOLLAR GENERAL	10
PRADA	26	KIA	9
ARMANI	19	FORD	8
VERSACE	18	EQUATE	7
FERRARI	17	FAMILY DOLLAR	7
LEXUS	16	SAVE-A-LOT	7
BENTLEY	15	HYUNDAI	6
BURBERRY	13	KROGER	6
AUDI	12	DOLLAR TREE	5
HERMES	11	FRUIT OF THE LOOM	5
LAMBORGHINI	11	LEE	5
CADILLAC	10	MARKET PANTRY	5
CARTIER	10	OLD NAVY	5
FENDI	10	RC COLA	5
NIKE	10	SHASTA	5
PORSCHE	10	TARGET	5
TIFFANY	9	HUNTS	4
RALPH LAUREN	8	KRAFT	4
ROLLS ROYCE	8	PEPSI	4
DOCLE AND GABBANA	7	STAPLES	4
JAGUAR	7	ACER	3
MICHAEL KORS	7	BIG LOTS	3
DIOR	6	CHEF BOYARDEE	3
SAMSUNG	6	CHEVY	3
MARC JACOBS	5	DODGE	3
MASERATI	5	FAYGO	3
MICROSOFT	5	FOREVER 21	3
SONY	5	GEORGE	3
ADDIDAS	4	LAYS	3
CHRISTIAN LOUBOUTIN	4	LEVIS	3
COCA COLA	4	PAYLESS	3
TAG HEUER	4	PAYLESS SHOES	3
TESLA	4	SAMSUNG	3
CALVIN KLEIN	3	SEARS	3
CELINE	3	SKETCHERS	3
GOOGLE	3	SUAVE	3
JORDANS	3	TACOBELL	3

Table A1 *Continued*

High status brands		Low status brands	
Brand name	Frequency	Brand name	Frequency
LEAR	3	WET N WILD	3
LINCOLN	3	WRANGLER	3
POLO	3	YUGO	3
YVES ST. LAURENT	3	AMERICA'S CHOICE	2
ACURA	2	BEST BUY	2
ALEXANDER WANG	2	BEST CHOICE	2
ANN TAYLOR	2	BOOST MOBILE	2
BULGARI	2	CASIO	2
CHLOE	2	CHEVROLET	2
COCO CHANEL	2	COCA COLA	2
CRISTAL	2	CONVERSE	2
DR DRE BEATS	2	COSTCO	2
GODIVA	2	CRYSTAL20	2
GUESS	2	CVS	2
HUGO BOSS	2	DANSKIN	2
J CREW	2	DE PINO'S	2
JIMMY CHOO	2	DELL	2
NIKKON	2	DOLLAR STORE	2
NORDSTROM	2	DR. THUNDER	2
NORTH FACE	2	ESSENTIAL EVERYDAY	2
OMEGA	2	FADED GLORY	2
RANGE ROVER	2	FILA	2
RAY BAN	2	FOLGERS	2
RITZ CARLTON	2	FUBU	2
TOM FORD	2	GAP	2
		GENERIC	2
		GIANT EAGLE	2
		GOOD VALUE	2
		GOODWILL	2
		H&M	2
		HANES	2
		KELLOG	2
		KOHL'S	2
		LOGITECH	2
		MALT-O-MEAL	2
		METRO PCS	2
		MILLVILLE	2
		PANTECH	2
		RADIO SHACK	2
		RAMEN	2
		RUSTLER	2
		SAM'S CHOICE	2
		SANYO	2
		UP & UP	2
		WENDYS	2
		WHITE CASTLE	2
		WHITE RAIN	2

Note. We excluded "Coach" from our list of top 10 high status brands because of its ambiguous meaning.

References

Alvarez-Cuadrado, F., & Attar, M. E. (2012). Income inequality and saving. *IZA Discussion Paper*. No 7083. Retrieved September 15, 2015, from http://ssrn.com/abstract=2196748.

Boyce, C. J., Brown, G. D. A., & Moore, S. C. (2010). Money and happiness: Rank of income, not income, affects life satisfaction. *Psychological Science*, *21*, 471–475. https://doi.org/10.1177/0956797610362671

Brown, G. D. A., Boyce, C. J., & Wood, A. M. (2015). The wellbeing-income gradient is steeper in more equal countries: Relative rank effects. Unpublished Manuscript.

Brysbaert, M., Warriner, A. B., & Kuperman, V. (2014). Concreteness ratings for 40 thousand generally known English word lemmas. *Behavior Research Methods*, *46*, 904–911. https://doi.org/10.3758/s13428-013-0403-5

Christen, M., & Morgan, R. M. (2005). Keeping up with the Joneses: Analyzing the effect of income inequality on consumer borrowing. *Quantitative Marketing and Economics*, *3*, 145–173. https://doi.org/10.1007/s11129-005-0351-1

Clark, A. E., Kristensen, N., & Westergård-Nielsen, N. (2009). Economic satisfaction and income rank in small neighbourhoods. *Journal of the European Economic Association*, *7*, 519–527. https://doi.org/10.1162/jeea.2009.7.2-3.519

Clark, A. E., & Oswald, A. J. (1996). Satisfaction and comparison income. *Journal of Public Economics*, *61*, 359–381. https://doi.org/10.1016/0047-2727(95)01564-7

Cynamon, B. Z., & Fazzari, S. M. (2013). *Inequality and household finance during the consumer age* (Levy Economics Institute No. 752).

Daly, M., Boyce, C., & Wood, A. (2015). A social rank explanation of how money influences health. *Health Psychology*, *34*, 222–230. https://doi.org/10.1037/hea0000098

Heffetz, O. (2011). A test of conspicuous consumption: Visibility and income elasticities. *Review of Economics and Statistics*, *93*, 1101–1117. https://doi.org/10.1162/rest_a_00116

Hirsch, F. (1977). *Social limits to growth*. London: Routledge.

Kawachi, I., Kennedy, B. P., Lochner, K., & Prothrow-Stith, D. (1997). Social capital, income inequality, and mortality. *American Journal of Public Health*, *87*, 1491–1498. https://doi.org/10.1084/jem.176.3.719

Layte, R., & Whelan, C. T. (2014). Who feels inferior? A test of the status anxiety hypothesis of social inequalities in health. *European Sociological Review*, *30*, 525–535. https://doi.org/10.1093/esr/jcu057

Luttmer, E. F. P. (2005). Neighbors as negatives: Relative earnings and well-being. *The Quarterly Journal of Economics*, *120*, 963–1002. https://doi.org/10.1093/qje/120.3.963

Lynch, J., Smith, G. D., Harper, S., Hillemeier, M., Ross, N., Kaplan, G. A., & Wolfson, M. (2004). Is income inequality a determinant of population health? *Milbank Quarterly*, *82*, 5–99. https://doi.org/10.1111/milq.2004.82.issue-1

OECD (2011). An overview of growing income inequalities in OECD countries: Main findings. *Divided We Stand Why Inequality Keeps Rising*, OECD 2011, 21–45. Retrieved September 15, 2015, from http://www.i-red.eu/resources/publications-files/oecd-divided-we-stand.pdf%5Cnhttp://egov.formez.it/sites/all/files/OCSE-An Overview of Growing Income Inequalities in OECD Countries.pdf.pdf

Perugini, C., Jens, H., & Collie, S. (2015). Inequality, credit expansion and financial crises. *Cambridge Journal of Economics*, MPRA paper, 1–31.

Pickett, K. E., & Wilkinson, R. G. (2010). *The spirit level: Why equality is better for everyone*. London: Penguin.

Ryoo, S., & Kim, Y. K. (2014). Income distribution, consumer debt and keeping up with the Joneses. *Metroeconomica*, *65*, 585–618. https://doi.org/10.1111/meca.12052

Saad, G. (2011). *Consuming instinct*. New York: Prometheus.

Schwartz, N. D. (2014). The middle class is steadily eroding. Just ask the business world. *The New York Times*, 5–9. Retrieved September 13, 2015, from http://www.nytimes.com/2014/02/03/business/the-middle-class-is-steadily-eroding-just-ask-the-business-world.html%5Cnhttp://www.nytimes.com/2014/02/03/business/the-middle-class-is-steadily-eroding-just-ask-the-business-world.html?_r=0

Stiglitz, J. E. (2012). *The price of inequality. How today's divided society endangers our future*. New York: WW Norton.

U.S. Census Bureau (2015a). GINI index of income inequality: 2010–2014 American Community Survey 5-year estimates. Retrieved March 7, 2015, from http://factfinder.census.gov/

U.S. Census Bureau (2015b). Household income in the past 12 months (in 2014 inflation-adjusted dollars): 2010–2014 American Community Survey 5-year estimates. Retrieved March 7, 2015, from http://factfinder.census.gov/

U.S. Census Bureau (2015c). Selected social characteristics in the United States: 2010–2014 American Community Survey 5-year estimates. Retrieved March 7, 2015, from http://factfiner.census.gov/

U.S. Census Bureau (2015d). Total population: 2008–2012 American Community Survey 5-year estimates. Retrieved March 7, 2015, from http://factfinder.census.gov/

U.S. Census Bureau (2015e). Urban and rural: Area facts. 2015 census congressional district summary file (113th Congress). Retrieved March 7, 2015, from http://factfinder.census.gov/

Walasek, L., & Brown, G. D. A. (2015). Income inequality and status seeking: Searching for positional goods in unequal U.S. States. *Psychological Science*, *26*, 527–533. https://doi.org/10.1177/0956797614567511

Walasek, L., & Brown, G. D. A. (2016). Income inequality, income, and internet searches for status goods: A cross-national study of the association between inequality and well-being. *Social Indicators Research*, *129*, 1001–1014. https://doi.org/10.1007/s11205-015-1158-4

Supporting Information

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Appendix S1. Methodological Details.