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Social Sampling Explains Apparent Biases in Judgments of Social Environments

Mirta Galesic[1], Henrik Olsson[1], and Jörg Rieskamp[2]
[1]Center for Adaptive Behavior and Cognition, Max Planck Institute for Human Development, Berlin, Germany, and [2]Department of Psychology, University of Basel

Abstract

How people assess their social environments plays a central role in how they evaluate their life circumstances. Using a large probabilistic national sample, we investigated how accurately people estimate characteristics of the general population. For most characteristics, people seemed to underestimate the quality of others' lives and showed apparent self-enhancement, but for some characteristics, they seemed to overestimate the quality of others' lives and showed apparent self-depreciation. In addition, people who were worse off appeared to enhance their social position more than those who were better off. We demonstrated that these effects can be explained by a simple social-sampling model. According to the model, people infer how others are doing by sampling from their own immediate social environments. Interplay of these sampling processes and the specific structure of social environments leads to the apparent biases. The model predicts the empirical results better than alternative accounts and highlights the importance of considering environmental structure when studying human cognition.

Keywords

self-enhancement, self-depreciation, social circle, regression, social-sampling model, social cognition, social perception

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The success of public-policy initiatives and business strategies is affected by people's willingness to spend or save, further their education, find a new job, develop their social connections, or invest in their health. This willingness, in turn, depends on people's evaluation of their financial circumstances, social status, and physical condition. To make such evaluations, people often compare themselves with others (e.g., Festinger, 1954; Suls, Martin, & Wheeler, 2002). How people assess the circumstances of others has important consequences for their willingness to change or maintain their own behavior. In the study reported here, we evaluated a simple computational model that predicts people's assessments of their social environments based on the underlying statistical structure of those environments and how people sample from them.

Social-cognition research has shown that people's perceptions of how they measure up against others are not accurate (Krueger & Funder, 2004). Across cultures, people appear to suffer from self-enhancement biases, such as the better-than-average and optimism biases, which lead them to believe they have better traits (e.g., friendliness, intelligence), abilities (e.g., driving), and future prospects than others do, or that their position among others is better than it actually is (Loughnan et al., 2011; Sedikides, Gaertner, & Toguchi, 2003; Wood, 1989). Such effects are considered to be among the most robust findings in the literature on social cognition (e.g., Alicke & Govorun, 2005; Chambers & Windschitl, 2004; Roese & Olson, 2007).

Why would people be consistently biased in representing their social environments? The dominant explanation is a *motivational bias*: People distort reality to improve their sense of self-esteem and well-being (Alicke, Klotz, Breitenbecher, Yurak, & Vredenburg, 1995). Another influential explanation is the *cognitive incompetence* of people who overestimate their social position (Kruger & Dunning, 1999). Yet neither account can explain findings of the opposite effect—self-depreciation, in particular for people who otherwise show superior skills (Burson, Larrick, & Klayman, 2006; Kruger, 1999; Moore & Small, 2007). To explain both self-enhancement and self-depreciation, several cognitive biases have been proposed (Chambers & Windschitl, 2004), but most of these suggestions involve redescriptions rather than explanations of the effects (Moore, 2007a).

Corresponding Author:
Mirta Galesic, Center for Adaptive Behavior and Cognition, Max Planck Institute for Human Development, Lentzeallee 94, 14195 Berlin, Germany
E-mail: galesic@mpib-berlin.mpg.de

It has been proposed that both self-enhancement and self-depreciation effects can be explained by a simple statistical artifact—regression (Fiedler, 1996; Krueger & Mueller, 2002; Moore & Small, 2007). This account assumes that people have an unbiased representation of the overall social environment but that their reports contain some random noise that leads to underestimation of high performance and overestimation of low performance. Regression in its pure form cannot explain the finding that worse-off people (e.g., those with bad results on a particular task) make larger errors than do better-off people (those with good results on a particular task; e.g., Burson et al., 2006; Ehrlinger, Johnson, Banner, Dunning, & Kruger, 2008; Krueger & Mueller, 2002; Kruger & Dunning, 1999). To remedy this shortcoming, researchers have proposed that systematic biases, such as a general better-than-average bias (Krueger & Mueller, 2002) or a test-difficulty bias (Burson et al., 2006), counteract or add to the regression effects. The origins of these supposed biases remain unclear. We propose a new model that predicts both self-enhancement and self-depreciation effects, as well as the differences in errors of better-off and worse-off people, without assuming any motivational or cognitive biases.

Social-Sampling Model

In our simple model, apparent self-enhancement and self-depreciation are caused by the interplay of the underlying *environmental structure* in people's lives and the *sampling processes* that people use. In Figure 1, we illustrate how the model works using excerpts from our empirical data and model predictions (both described in more detail later). Two properties of the environmental structure play a major role. First, different population characteristics have different frequency distributions (Fig. 1a). Although most people are doing

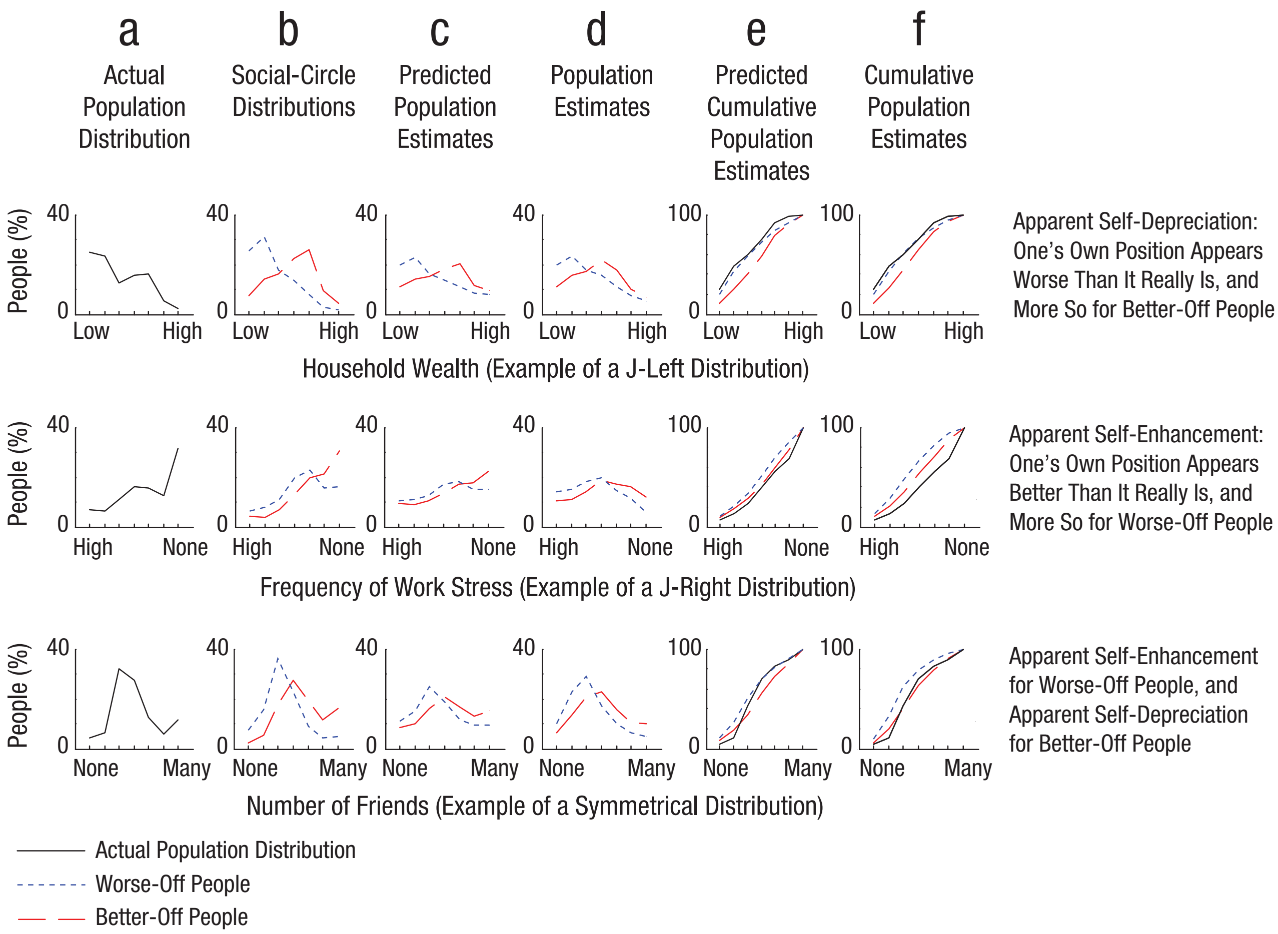

Fig. 1. Empirical data and predictions of the social-sampling model for 3 of 10 studied characteristics of the Dutch population: household wealth (example of a J-left distribution), frequency of work stress (example of a J-right distribution), and number of friends (example of a symmetrical distribution). The first column (a) shows the actual population distributions of the three characteristics. The second column (b) presents participants' estimated distributions within their social circles, separately for worse-off and better-off people (i.e., those positioned at the three lowest and three highest levels of each characteristic, respectively). The third column (c) shows the social-sampling model's predictions for better-off and worse-off people's estimates of the population distributions. The fourth column (d) shows better-off and worse-off people's estimates of the population distributions. The fifth column (e) presents the model's predictions for better-off and worse-off people's estimates of the cumulative population distributions; the final column (f) shows better-off and worse-off people's estimates of the cumulative population distributions.

well in respect to some characteristics (e.g., frequency of work stress), most are doing less well in respect to other characteristics (e.g., household wealth). When distributions are plotted so that *x*-axes always range from negative to positive levels of a characteristic (as in all figures in this article), they have a J-right shape when most people are doing well and a J-left shape when most people are doing poorly. The distributions are relatively symmetrical when most people are at middle levels.

Second, most social environments are spatially clustered: People with similar characteristics tend to live close to each other and move in similar social circles. This tendency toward homophily is a well-known property of social worlds (McPherson, Smith-Lovin, & Cook, 2001). Social circles of people who are relatively worse off on certain characteristics tend to include somewhat more people who are in a similar position than do social circles of people who are relatively better off (Fig. 1b).

These aspects of environmental structure interact with two aspects of sampling processes that people engage in when estimating properties of their social environment. First, people are unlikely to draw representative samples of the overall social environment (i.e., the general population). Instead, as has been proposed previously (Fiedler, 2000; Hertwig, Pachur, & Kurzenhäuser, 2005; Lichtenstein, Slovic, Fischhoff, Layman, & Combs, 1978; Pachur, Rieskamp, & Hertwig, 2005; Ross, Greene, & House, 1977), they rely on available samples—their social circles. These typically include family, friends, and acquaintances they meet on a regular basis. Second, when people extrapolate from their social circles to the general population, they tend to smooth extreme peaks and valleys of their social-circle distributions. Reflecting these two aspects of the sampling process, both predicted (Fig. 1c) and empirically obtained (Fig. 1d) population estimates resemble smoothed social-circle distributions (Fig. 1b; see Fig. S1 in the Supplemental Material available online for more examples).

Smoothing can occur for several reasons alone or in combination. A certain amount of smoothing can occur because of noise inherent in response or retrieval processes (Juslin, Winman, & Olsson, 2000). This corresponds to the reliability parameter in the regression framework. It is also possible that people make deliberate adjustments to account for the fact that social circles tend to include people who are similar to each other and therefore are likely to include more extreme proportions of particular characteristics than are found in the general population. Finally, people's assessments could follow an updating process in which an initial judgment represented by a uniform prior distribution—often implemented as the first step in probabilistic models of cognition (Chater & Oaksford, 2008)—is updated by information from one's own social circle. All three processes could lead to a smoothing effect.

The social-sampling model is formalized as follows:

$$PE_i = (SC_i - \overline{SC}) \times s + \overline{SC},$$

where PE_i is a person's estimate of the percentage of the general population belonging to level *i* of a certain characteristic, SC_i is the percentage of that person's social circle belonging to level *i*, and $\overline{SC}$ is the average percentage across all levels of that person's social circle for that characteristic. The parameter *s* reflects the smoothing of the social-circle distributions that occurs when they are used to estimate population distributions. The larger the parameter value, the lower the amount of smoothing. Smoothing moves all estimates toward their average ($\overline{SC}$). For instance, when a person estimates the percentage of the general population belonging to the lowest level of income (PE_1), the model predicts that this estimate will be based on the percentage of that person's social circle at the lowest level of income (SC_1), adjusted toward the mean percentage across all levels ($\overline{SC}$; if there are seven levels of income, $\overline{SC} = 100/7 = 14.3$). For example, if 10% of a person's social circle belong to the lowest level of income, this leads to a predicted percentage of 12.1 for the general population, using a smoothing parameter value of $s = .5$ (i.e., $(10 – 14.3) \times 0.5 + 14.3 = 12.1$, as in Figs. 1c and 1e). This procedure can be applied for all other levels of income.

The social-sampling model makes two important predictions. First, because of the interplay of the shapes of population distributions and the smoothing of social-circle distributions, people's population estimates will appear as if they were affected by self-enhancement when the underlying distribution of the general population has a J-right shape (i.e., when most people are doing well) and by self-depreciation when the underlying distribution has a J-left shape (when most people are doing badly). Figure 1e illustrates this with cumulative versions of the distributions in Figure 1c. Cumulative distributions enable comparison between percentile ranks of the same individual in actual and estimated population distributions. Note that the model's predictions of estimated population distributions in Figure 1e are above the actual population distributions for J-right distributions but below the actual population distributions for J-left distributions. This means that one's estimated percentile rank in the general population appears to be higher than it actually is for the J-right distributions (resulting in apparent self-enhancement) and lower than it actually is for the J-left distributions (resulting in apparent self-depreciation).

Second, because of the interplay of spatial clustering of social environments and people's reliance on social circles when estimating population distributions, the model predicts that when the underlying distribution has a J-right shape, the errors of population estimates of the worse-off people will be larger—toward more apparent self-enhancement—than the errors of the better-off people will be (Fig. 1e). This is because the social circles of worse-off people will tend to include more people who are also doing badly, and, consequently, they will overestimate the frequency of worse-off people in the general population. The reverse is predicted when the underlying distribution has a J-left shape: Here, the errors of worse-off people will be smaller than the errors of better-off people (Fig. 1e).

To test the predictions of the social-sampling model, we collected data from a large, probabilistic, nationally representative sample of Dutch citizens. This sample enabled us to investigate self-enhancement and self-depreciation effects in the general population, in contrast to the convenient samples of students of elite universities that many previous studies have relied on (cf. Burson et al., 2006). It also enabled us to obtain valid population benchmarks to evaluate participants' population estimates. In most previous studies, participants were asked about groups of "average students" or "average persons" (e.g., Alicke et al., 1995; Kruger & Dunning, 1999; Loughnan et al., 2011), but their estimates were compared with benchmarks calculated from empirical data taken from the other participants in that particular study, not from a representative sample of students or from the general population.

Method

Participants

The sample of participants was drawn from 5,000 Dutch households participating in the Longitudinal Internet Studies for the Social Sciences (LISS) panel (raw data for the sample are available at www.lissdata.nl/dataarchive/study_units/view/54). The panel is based on a probability sample of households drawn from the population register by Statistics Netherlands. Each household is provided with a computer and Internet connection. The study was conducted in two waves 3 months apart: 1,646 participants completed the first wave, and 1,416 completed the second wave. The sample was representative of the Dutch population 15 or more years of age in terms of gender, age, education, and income (Table 1).

Materials and procedure

In the first wave, participants answered questions about 10 characteristics related to their own financial situation, love life, friendships, health, work stress, and education (e.g., "What is your highest level of education?"; text for all questions and the number of participants who gave valid responses to each question can be found in Question Texts and Table S1, respectively, in the Supplemental Material). All questions were presented in randomized order on 7-point fully labeled scales. From the answers, we derived actual population distributions. The participants also estimated the distributions of these characteristics in the general population of The Netherlands (e.g., "What percentage of adults living in The Netherlands fall into the following categories?"). Following Nisbett and Kunda (1985), we asked participants to estimate the whole distribution of different characteristics of other people rather than just a summary indicator, such as the mean. This allowed us to examine the discrepancies between estimated and actual distributions in detail. Participants used an interactive online

Table 1. Characteristics of the Sample (N = 1,646) and the Dutch Population

Characteristic	Sample: Unweighted *n*	Sample: Weighted percentage[a]	Actual population percentage
Sex			
Male	746	49.1	49.1
Female	900	50.9	50.9
Age			
15–24 years	191	10.4	14.7
25–44 years	523	35.6	34.1
45–64 years	705	35.7	33.3
65+ years	227	18.3	17.9
Education[b]			
Minimum compulsory education	99	10.9	8.9
Higher general, preparatory scientific, or middle-level applied education	267	23.7	24.3
Higher applied education	707	39.4	41.4
University degree or higher	419	15.8	15.9
Net household income[b]			
Up to €20,000	294	33.4	30.9
€20,001–€40,000	770	42.6	43.7
€40,001–€60,000	376	16.6	17.7
More than €60,000	88	7.4	7.7

[a]To obtain realistic estimates of population distributions from the sample data, we applied poststratification weights based on sex, age, education, marital status, and disposable household income using data from Statistics Netherlands. The weights were calculated using a multiplicative weighting procedure that involved iterative proportional fitting (or raking; see Bethlehem, 2002). [b]Not all participants gave valid responses regarding their education and household income.

interface to allocate each characteristic across seven levels totaling 100% of the Dutch population (see Fig. S2 in the Supplemental Material). A running tally and a dynamic bar chart were provided as aids.

By comparing participants' position in the actual population distribution with their position in their estimated population distribution, we could infer whether they overestimated or underestimated their actual position in the general population. This indirect method of investigating people's assessments of their social position is often used in studies of social comparison (Chambers & Windschitl, 2004). Although this method does not ask for explicit comparisons with other people, it has produced consistent, though smaller, self-enhancement and self-depreciation effects than more direct methods have (Chambers & Windschitl, 2004; Klar & Giladi, 1997; Moore, 2007b).

In the second wave, the same participants were asked to estimate the distributions of the same characteristics in their own social circle (e.g., "What percentage of your social contacts fall into the following categories?"), using the same interface. We defined social contacts as "adults you were in personal, face-to-face contact with at least twice this year, [such as] your friends, family, colleagues, and other acquaintances." We asked for face-to-face contact to tap into the spatial clustering of social environments that we hypothesized plays a role in the social-sampling model. In both waves, participants also answered questions about their well-being (results for these measures are not presented here). The Ethics Committee of the Max Planck Institute for Human Development approved the study.

Results

The results shown in Figure 2 suggest that most participants had rather accurate representations of their immediate social environments. Although participants had very different social circles (see Fig. S1 in the Supplemental Material), average social-circle distributions followed the actual population distributions more closely than did the average estimates of population distributions. Because our sample was representative of the general population, the fact that average social-circle distributions resembled the actual population distributions suggests that there was little or no systematic deviation in participants' reports of their social circles. In contrast, people's estimates of the general population were less accurate and therefore suggest systematic deviations.

First, we observed both apparent self-enhancement and self-depreciation effects, depending on the characteristic. As Figure 2 illustrates, self-enhancement effects occurred for the characteristics with J-right distributions (e.g., household income, conflicts with partners, and health problems), that is, when most people were doing well. For these characteristics, people overestimated the relative frequency of the negative end of the scale and underestimated the relative frequency of the positive end, which made their own position look better than it really was. Self-depreciation effects occurred for the three characteristics whose distributions were J-left shaped (personal income, household wealth, and number of dates), that is, when most people were doing badly. For these characteristics, people overestimated the relative frequency of the positive end of the scale and underestimated the relative

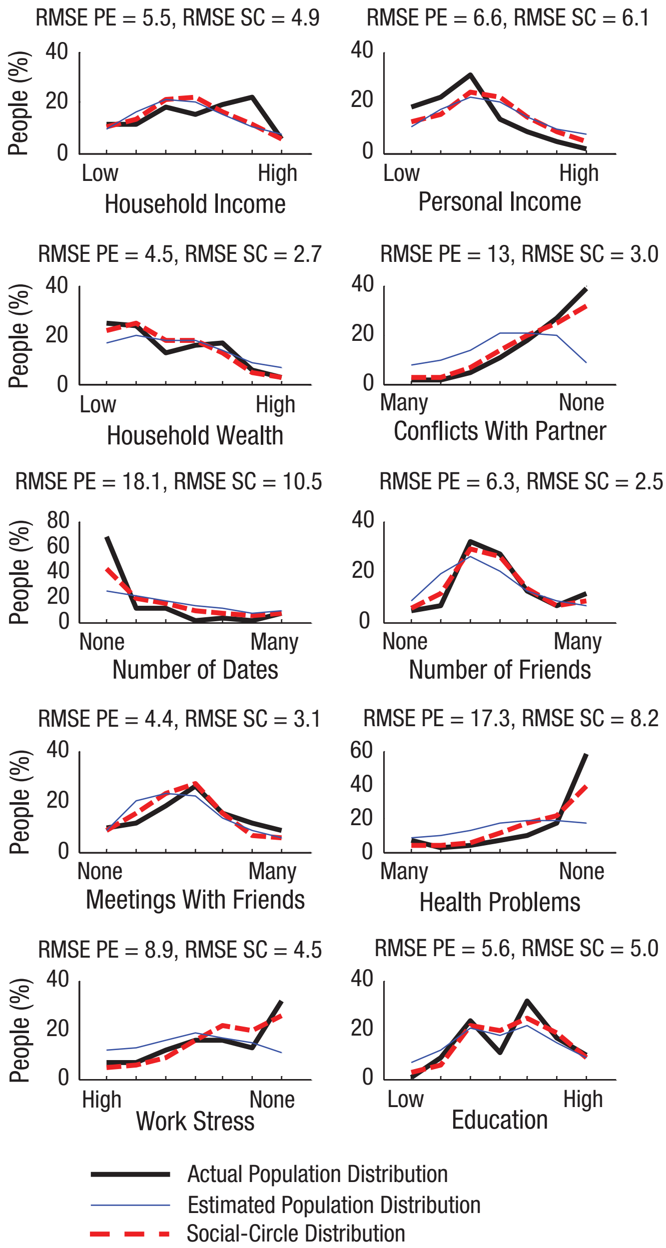

Fig. 2. Actual population distributions, average estimated population distributions, and average social-circle distributions for the 10 characteristics. Each graph shows the actual population distribution, average estimated population distribution, and average distribution within participants' social circle for one of the characteristics. All *x*-axes range from negative to positive levels of the given characteristic. The root-mean-square errors (RMSEs) indicate the deviation of the population estimates (PEs) and social-circle (SC) distributions from the actual population distributions.

frequency of the negative end, which made their own position look worse than it really was.

Second, we observed that the deviations of estimated and actual population distributions depended on individuals' position on the given characteristic. For most J-right distributions, worse-off people made larger errors and appeared to self-enhance more than did better-off people (Fig. 3). For the three J-left distributions, better-off people made equal or larger errors, thus appearing to self-depreciate more than worse-off people did. The social-sampling model is the only account that can predict this pattern of results, as illustrated in the next section.

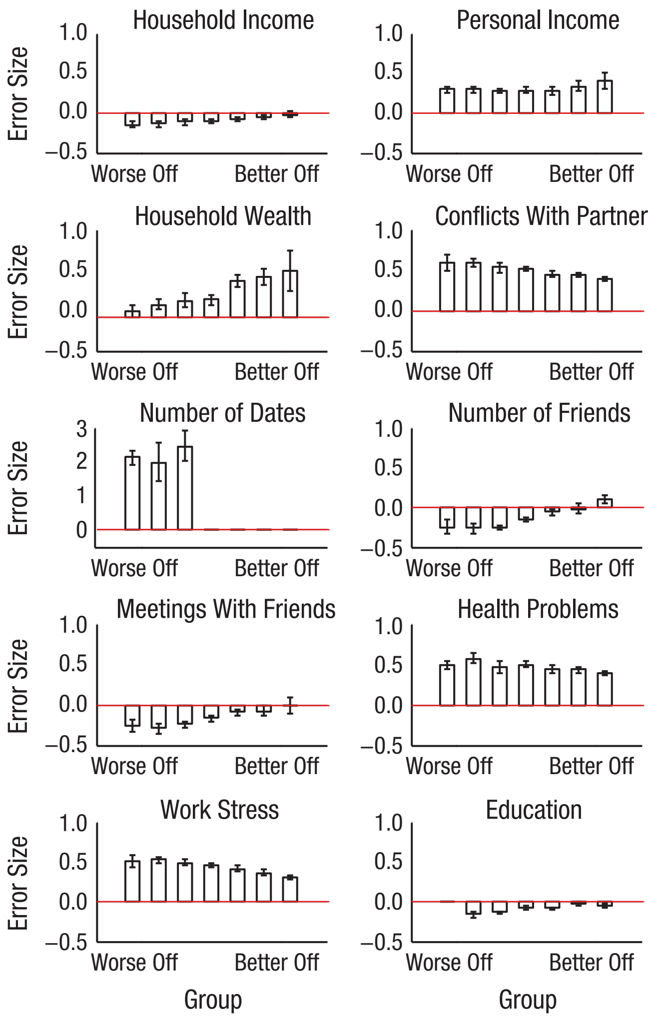

Fig. 3. Average errors of estimated population means for the 10 characteristics. Results are presented separately for groups of participants at different levels of each characteristic (from those who are worse off to those who are better off). For each individual and characteristic, error size was calculated using the following formula: (estimated mean – actual mean)/actual mean. Error bars denote ±2 *SE*. Groups with fewer than 10 observations are omitted.

Model Comparison

For simplicity and to avoid overfitting, we set *s* in the social-sampling model to an intermediate value of 0.5 and evaluated the model's predictions at the aggregate level with the average estimated population distributions. The predictions of the social-sampling model (illustrated in Figs. 1c and 1e) corresponded well with the observed results (see Figs. 1d and 1f, 2, and 3). For J-right distributions, we predicted and observed a self-enhancement effect, and for J-left ones, we predicted and observed a self-depreciation effect. In addition, worse-off people appeared, as predicted, to enhance their position more (or depreciate it less) than did better-off people. The motivational account—that people distort reality to improve their well-being—cannot explain the self-depreciation effects. The cognitive-incompetence account—that people with less favorable characteristics make larger errors when estimating their social environments—is also not supported: For J-left distributions, the better-off people—those with higher personal income and household wealth and those who went on more dates—made similar or larger errors than did worse-off people. The pure-regression account can explain both self-enhancement and self-depreciation effects but cannot explain the discrepancies in errors of better-off and worse-off people without introducing additional biases, because it makes the same predictions for both groups.

To examine these qualitative findings in more detail, we compared predictions of the social-sampling model with predictions of the regression model, the only other model that makes quantitative predictions. We set the parameter that regulates the amount of regression to a fixed value of 0.5 to predict average estimated population distributions (see Fig. S3 in the Supplemental Material), cumulative estimated population distributions (see Fig. S4 in the Supplemental Material), and estimated population means (see Fig. S5 in the Supplemental Material). For both better-off and worse-off people, the social-sampling model predicted data patterns consistently better than the regression model did. For instance, the correlations between average predicted and estimated population distributions were higher and root-mean-square errors were lower for the social-sampling model for all 10 characteristics for worse-off people and for 7 out of 10 characteristics for better-off people. This result was not limited by the models' a priori set parameter values. When we estimated the models' parameters from data and tested their predictions with a cross-validation procedure, we obtained the same pattern of results (see Model Comparison in the Supplemental Material for details).

Discussion

We found that people were, on average, rather accurate in assessing their social environments, but they showed some systematic deviations. Depending on the characteristic, we found apparent self-enhancement and self-depreciation effects, and people who were doing poorly tended to enhance their position more or depreciate it less than those who were better off. Although these results appear to suggest a motivational or a cognitive bias, they were predicted by a simple social-sampling model that assumed an unbiased mind acting within a particular environmental structure. That people are well attuned to their immediate social environments but not as well to broader society (Fig. 2) can be considered adaptive: It is one's social circle, not the "general population" or an "average person" that should have the biggest influence on one's happiness and aspirations. In addition, using social circles to estimate population distributions is an effective strategy when the latter are unknown, particularly when people are aware that their social circles are not representative of the overall population.

The present results are consistent with Nisbett and Kunda's (1985) finding that people can provide relatively accurate estimates of social distributions. In addition, our results and model support Nisbett and Kunda's contention that people have reasonably accurate memories of the positions of at least several other people on a given characteristic and that they use this knowledge when estimating population distributions. Our results support the suggestion that people's superior information about themselves compared with their information about other people can explain apparent biases (e.g., Fiedler, 1996; Moore & Healy, 2008; Moore & Small, 2007). One major difference between our model and previously proposed differential-information theories (Moore & Healy, 2008; Moore & Small, 2007) is that our model predicts estimations for whole distributions based on social circles, and the differential-information theories assume that people use information about themselves when predicting characteristics of other persons. Further, the differential-information theories have not been tested quantitatively.

Our results are also in line with findings showing that people use their social circles to make judgments about frequencies of health risks in the general population (Hertwig et al., 2005; Pachur et al., 2005). The sampling process in the social-sampling model resembles the regressed version of the so-called availability-by-recall mechanism (Hertwig et al., 2005), according to which people judge that the more prevalent of two risks in their social circle is also more prevalent in the general population. Our model goes further by predicting estimates of whole distributions rather than just binary judgments. In addition, in the social-sampling model, the sampling process is only one component, the other being environmental properties. The interplay between these two components is essential for our model. Although the importance of studying how the environment interacts with the mind has been recognized for many years (Brunswik, 1955; Simon, 1956), these ideas have only recently been applied more generally in psychological research (Denrell, 2005; Fiedler, 2000; Fiedler & Juslin, 2006; Gigerenzer, Todd, & the ABC Research Group, 1999; Juslin, Winman, & Hansson, 2007; Stewart, Chater, & Brown, 2006).

Our model provides a novel and parsimonious explanation for why many previous studies have found that people are prone to self-enhancement and why people with low test scores make larger errors than do people with high test scores (e.g., Burson et al., 2006; Ehrlinger et al., 2008; Krueger & Mueller, 2002; Kruger & Dunning, 1999). In most studies, the population that participants had to compare themselves with was broader than their social circle—typically other students at the same university. According to the social-sampling model, this leads to population estimates resembling smoothed versions of social circles. These sampling processes interact with the second property of previous studies: In most of them, the majority of participants scored relatively well. According to our model, the resulting J-right distribution in combination with the sampling processes leads to an overall self-enhancement effect. In addition, students with low scores—who are under the assumption that their circle of friends includes somewhat more people similar to themselves than the general population does— will overestimate the frequency of other participants with low scores more than students with high scores will. Therefore, they will appear to self-enhance more than the students with high scores will. Only for truly difficult tests—when the majority of participants score low—will most participants appear to underestimate their position, with those who score high now making larger errors than those who score low (cf. Burson et al., 2006). Note that our model can be applied not only to indirect but also to direct comparisons given the (reasonable) assumption that, when estimating their position among others, people first form a representation of how others are doing.

The social-sampling model captures some of the basic aspects of how people represent their social environments. Of course, other processes might also be involved. Some people could have a rough idea of the shape of the true population distribution and combine it with what they know about their immediate social environments (Nisbett & Kunda, 1985). For instance, well-educated people in our sample seem to have had a rather good idea of what the overall population distribution of education levels looks like (see Fig. S3 in the Supplemental Material). Furthermore, when characteristics are vaguely defined (e.g., work stress) or are not publicly observable (e.g., conflicts with partners), it can be difficult to use social-circle information. In that case, people might use their own position for population estimates, perhaps combined with an expectation that natural phenomena are normally distributed (Nisbett & Kunda, 1985). Subjective biases in estimating one's social circle may also play a role. For instance, some participants may have thought that people in their social circles are more similar to themselves than they really are. Such beliefs can even be helpful when predicting others' behavior (Dawes & Mulford, 1996). Finally, different methods of assessing distributions (e.g., using direct rather than indirect methods, or using summary indicators rather than whole distributions) might induce various motivational or cognitive biases. Statistical artifacts specific to direct assessments may have contributed to the effects observed in other studies (Harris & Hahn, 2011).

We have provided a novel computational model that can explain both self-enhancement and self-depreciation effects and that gives specific quantitative predictions about the direction and size of these effects in different population groups. Our explanation highlights the importance of studying both people's inference processes and their environments to obtain a more complete picture of the nature of human cognition.

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Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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Supplemental Material

Additional supporting information may be found at http://pss.sagepub.com/content/by/supplemental-data

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