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A Sampling Model of Social Judgment

Mirta Galesic
Santa Fe Institute, Santa Fe, New Mexico, and Max Planck Institute for Human Development, Berlin, Germany

Henrik Olsson
Santa Fe Institute, Santa Fe, New Mexico, and University of Warwick

Jörg Rieskamp
University of Basel

Studies of social judgments have demonstrated a number of diverse phenomena that were so far difficult to explain within a single theoretical framework. Prominent examples are false consensus and false uniqueness, as well as self-enhancement and self-depreciation. Here we show that these seemingly complex phenomena can be a product of an interplay between basic cognitive processes and the structure of social and task environments. We propose and test a new process model of social judgment, the social sampling model (SSM), which provides a parsimonious quantitative account of different types of social judgments. In the SSM, judgments about characteristics of broader social environments are based on sampling of social instances from memory, where instances receive activation if they belong to a target reference class and have a particular characteristic. These sampling processes interact with the properties of social and task environments, including homophily, shapes of frequency distributions, and question formats. For example, in line with the model's predictions we found that whether false consensus or false uniqueness will occur depends on the level of homophily in people's social circles and on the way questions are asked. The model also explains some previously unaccounted-for patterns of self-enhancement and self-depreciation. People seem to be well informed about many characteristics of their immediate social circles, which in turn influence how they evaluate broader social environments and their position within them.

Keywords: social judgment, false consensus, false uniqueness, self-enhancement, self-depreciation

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Social judgments are ubiquitous in everyday life and form the basis for many aspects of social cognition: social comparison to determine one's own relative performance and establish personal goals ("How many of my colleagues have a higher income than I have?"), social learning about the value of unknown options ("How many other people with diabetes have bought this type of health insurance?"), formation of social norms and values ("How many other students drink more than I do?" or "How many of my family members support this political party?"), coordination ("How many other drivers will take the same route to the city center?"), and cooperation ("How many other people in the general population recycle?"). The central goal of the present work is to provide a better understanding of the cognitive processes underlying such judgments.

There is a large literature in social psychology on different phenomena associated with social judgment, sometimes leaving an impression that social cognition is fraught with biases that prevent people from fully understanding and adapting to their social environments (Krueger & Funder, 2004). Prominent examples are false consensus (where endorsers of a particular view believe that this view is *more* common than nonendorsers believe), false uniqueness (where endorsers of a particular view believe that this view is *less* common than nonendorsers believe), self-enhancement (where people overestimate their performance relative to others), and self-depreciation (where people underestimate their performance relative to others). Past accounts of these effects have mostly focused on cognitive and motivational processes within the mind. However, seemingly complex phenomena can be a product of an interplay between minds and their social and task environments

Mirta Galesic, Santa Fe Institute, Santa Fe, New Mexico, and Center for Adaptive Behavior and Cognition and Harding Center for Risk Literacy, Max Planck Institute for Human Development, Berlin, Germany; Henrik Olsson, Santa Fe Institute, and Department of Psychology, University of Warwick; Jörg Rieskamp, Department of Psychology, University of Basel.

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Correspondence concerning this article should be addressed to Mirta Galesic, Santa Fe Institute, 1399 Hyde Park Rd, Santa Fe, NM 87501. E-mail: galesic@santafe.edu

(cf. Simon, 1996). In the present work we describe a new process model of social judgment that provides a parsimonious quantitative account of these phenomena, and shows that they occur when relatively simple cognitive processes interact with structural properties of social and task environments.

In what follows, we first describe the new model, the social sampling model (SSM). We then relate it to the existing theoretical and methodological approaches to social judgment. This is followed by tests of a number of the SSM's assumptions. Next, we show how the SSM can simultaneously explain false consensus and false uniqueness, as well as self-enhancement and self-depreciation. We end by discussing theoretical and practical implications of our results.

The Social Sampling Model

In the SSM, social judgments result from the processes of sampling social instances from memory, operating in a particular structure of social and task environments. In this regard the model follows the tradition of other ecological approaches to cognition (e.g., Anderson, 1990; Fiedler & Juslin, 2006; Gigerenzer, Todd, & the ABC Research Group, 1999; Hertwig, Hoffrage, & the ABC Research Group, 2013). We investigate how well people's social judgments can be approximated with the SSM, while recognizing that other cognitive and motivational processes can act in conjunction with the sampling processes described in the SSM. The model goes beyond existing models of social judgment, including our own previous work (Galesic, Olsson, & Rieskamp, 2012; see section Relationship to Previous Work), by providing a process-based account and quantitative predictions of different types of judgments and explaining several phenomena that were previously theoretically disconnected.

Structure of Social and Task Environments

The SSM describes people's judgments of frequency distributions of different characteristics of their social environments. Two properties of social environments shape the social information people rely on for their judgments. First, social environments are characterized by *homophily*: People with similar characteristics tend to live close to each other and move in similar social circles (McPherson, Smith-Lovin, & Cook, 2001). Seeking phenotypically similar cooperation partners has been shown to be evolutionary adaptive in a wide range of circumstances and has been observed throughout the animal kingdom (Fu, Nowak, Christakis, & Fowler, 2012). Homophily is higher for some characteristics, in particular for race and ethnicity, age, religion, and socioeconomic status. It is also higher in some social circles than in others: Some people have tightly knit networks that are quite homogeneous in terms of characteristics such as income or political beliefs, while others have looser networks whose members are connected with weaker and longer links and have more heterogeneous characteristics. Homophily appears to be driven both by selective attraction to similar others and by people's tendency to adopt beliefs and behaviors of those who surround them (e.g., Christakis & Fowler, 2007, 2008). We show that homophily alone can explain when false consensus versus false uniqueness are expected to occur.

The second important property of social environments is that different characteristics have different frequency distributions: Some, such as income and health problems, have highly skewed distributions, while others such as number of friends or education are more normally distributed (Galesic et al., 2012; Nisbett & Kunda, 1985; see also Roy, Liersch, & Broomell, 2013, for examples of the importance of distribution shape in social judgments). We show that this property can produce seemingly very different phenomena (self-enhancement vs. self-depreciation) when interacting with otherwise equivalent cognitive processes.

Besides social environments, task requirements can influence the size and direction of judgment effects. For example, question phrasing and response formats can substantially alter the set of considerations people evoke when thinking about an issue and consequently their answers (Tourangeau, Rips, & Rasinski, 2000). We will demonstrate that just by using different response formats one can induce either false-consensus or false-uniqueness effects for the same questions, and that this can be predicted by the SSM.

Social Sampling Processes

According to the SSM, people derive their social judgments by sampling relevant instances of their social environments from memory. Most of the instances come from people's social circles—family, friends, and acquaintances they meet regularly. Broader social environments—such as various out-groups or the general population—are rarely experienced directly. To make judgments about characteristics of such groups, people sample instances that belong to or are similar to the members of that group (the *reference class*) and determine how many of them have a certain characteristic.

The sampling process results in two layers of activation of social instances in memory. Instances receive one layer of activation if they belong to or are similar to the reference class. This process resembles the mechanisms assumed by exemplar-based models of social judgment (e.g., Linville, Fischer, & Salovey, 1989; E. R. Smith & Zarate, 1992). The activated instances constitute the *sample*. Another layer of activation occurs if instances of the sample have the *target characteristic* (e.g., higher income, drinking excessively, recycling). Thereafter, the sum of activations representing the target characteristic is compared to the sum of activations representing the sample, and their ratio is expressed in the format required by the task (e.g., as a numerical ratio or as a percentage).

More formally, the estimated proportion of members of a reference class, R, who have a certain characteristic, C, can be defined as

$$p(C|R) = \frac{\sum_{i=1}^{n} \alpha \times A_{Ci} \times A_{Ri}}{\sum_{i=1}^{n} A_{Ri}} \tag{1}$$

where A_{Ci} is the activation of instance i due to having a target characteristic C ($A_{Ci} = 1$ if it has the characteristic, 0 otherwise) and A_{Ri} is the activation of instance i due to belonging to the reference class R ($A_{Ri} = 1$ if it is in the reference class, 0 otherwise).[1] The denominator constitutes the sample: those instances of the social environment available in memory that are activated because of their similarity to the reference class. The numerator consists of those instances in the sample that are activated because they additionally have the target characteristic. The *recall probability parameter* α represents general memory activation: Among all instances in the sample, those instances that have characteristic C are activated with a probability α. In essence, parameter α formalizes the idea that there is noise in memory-activation levels. Variants of this idea are routinely implemented in memory models and cognitive architectures such as ACT-R (e.g., Anderson & Lebiere, 1998).

Unlike some related approaches (Fiedler, 2000; Juslin, Winman, & Hansson, 2007), we do not assume that people neglect the fact that the social information they have is typically a biased subset of the broader social environment. As noted by Juslin, Winman, and Hansson (2007), the extent of this "cognitive myopia" might be limited, as in everyday life people are often aware that the instances they encounter are not a representative sample of the general population. We therefore assume that people attempt to sample those instances from memory that are in some way similar to the reference class they are asked about. To select those instances, people use sampling cues that are correlated with instances' membership in the reference class. Some reference classes have visible cues such as gender or geographical location that can be used to determine whether an instance should be included in the sample. To illustrate, if the reference class includes people living in the United States, or students at another university, the instances in one's memory who live in Sweden, or attend one's own university, should have a lower probability of being activated. For other reference classes such as "other students," "average persons," or "the general population" it may be less obvious whether an instance should be included in one's sample. In these cases, a valid cue may be similarity of an instance to oneself according to the characteristic in question. This similarity cue exploits the fact that most social environments are characterized by homophily. If one selects those instances in one's social environment that are least similar to oneself, one increases the chances that the resulting sample will represent broader social environments beyond one's immediate social circle. For example, when estimating what percentage of the general population supports a particular party, it is reasonable to disregard instances from one's immediate social environments who have the most similar political beliefs as oneself. Or, when estimating how many other students on campus drink more than oneself, one might disregard some of the frequent visitors to the same bar where one is a regular. We provide empirical evidence for this mechanism in the section Testing the SSM's Assumptions.

These ideas about sampling are formalized in the SSM by assuming that only ρ instances most similar to the reference class are activated and become part of the sample:

$$A_{Ri} = 1 \text{ if } pct_i \leq \rho, \text{ else } A_{Ri} = 0, \tag{2}$$

where pct_i is the percentile of instance i among all n instances sorted by their similarity to the reference class R from highest to lowest, and the *similarity parameter* ρ is the percentile of the least similar instance that is still included in the sample. In essence, $1 - \rho$ instances that are least similar to the reference class are not activated. Higher values of ρ mean that larger proportion of all instances of the social environment that are stored in memory are activated and included in the sample. Both the recall probability parameter α and the similarity parameter ρ are free parameters and can take any value between and including 0 and 1. The values of ρ and α may vary depending on the task or social environment, as well as across persons (although in the present paper we do not model individual differences). Sensitivity analyses in the supplementary online material 1 suggest that the model is not overly flexible and that SSM predicts qualitatively similar patterns of results for most realistic sets of parameters.

As a first approximation, we do not assume that relevant social instances are explicitly counted or even consciously activated. This is in line with other cognitive models of human judgment (e.g., Kruschke, 1992; Nosofsky, 1986). Instead, judgments are the result of an impression about the relative size of the part of the sample that has a particular characteristic. This can be a vague non-numerical and even nonverbal impression that is transformed to percentages or another appropriate format only in the final response stages (Tourangeau et al., 2000). Depending on the assumptions of the underlying cognitive architecture, the same process could be implemented sequentially or in parallel (Townsend & Wenger, 2004). The implementation could have different consequences for the cognitive limitations that may influence the sampling process. For instance, if the activation of instances occurs sequentially and consciously, working memory capacity may restrict the sample to a relatively small number of instances. In contrast, if the sampling process does not take place consciously or occurs in a parallel fashion, then a large sample of instances could be activated.

Examples

To demonstrate how the model works, imagine that every person in a population votes for either a red or a blue party (Figure 1A). Assume that a person who votes red is asked about the percentage of people who also vote red in the general population, and that the correct answer is 60% (the population column in Figure 1A). Here, the reference class R is the general population and the target characteristic C is voting for the red party. Our person will have a number of instances from her social environment stored in memory. Assuming a moderate degree of homophily for this characteristic, this red voter is likely to have encountered and memorized a somewhat larger percentage of red voters than there are in the general population (the social circle column in Figure 1A). In this example, a red voter has 72% red voters in their social circle, corresponding to Coleman Index of homophily of .3 (the difference between percentage of red voters in the social circle of red voters and the percentage of red voters in an average social circle, divided by the percentage of blue voters in an average social circle; Coleman, 1958; Signorile & O'Shea, 1965). To sample instances that are most likely to be informative of the general population, she discards 10% of her memorized social circle, including those most similar to herself, and assumes that the remaining 90% of the instances are sufficiently similar to the reference class (i.e., similarity parameter ρ = .9). In this case, all of the discarded instances are voting red and as a result her sample

[1] For simplicity, we assumed only binary values of A_{Ci} and A_{Ri}, but the model can easily incorporate other activation values.

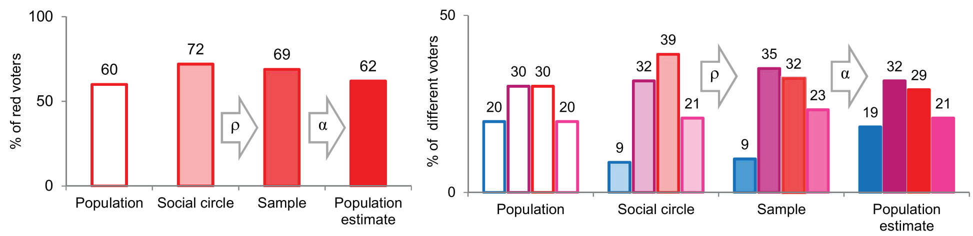

Figure 1. (A) Example of social sampling process when population includes two levels of the target characteristic (voters of red and blue parties). The red voter is asked "What percentage of the general population will vote red?" (B) Example of social sampling process when population includes four levels of the target characteristic (voters of blue, purple, red, and pink parties). Here, the red voter is asked "What percentage of the general population will vote for each of the four parties?" See the online article for the color version of this figure.

will include 69% red voters (the sample column in Figure 1A). Finally, to give her estimate, the person relies on who in her sample has the target characteristic of voting red. We assume that memory activation of persons in her sample is less than perfect (i.e., recall probability $\alpha = .9$), so she does not activate all of the instances in her sample who vote red. The resulting impression about the prevalence of a characteristic can be expressed as a numerical ratio (two in three people) or as a percentage of the reference class (62% of people, as in the population estimate column in Figure 1A). Here we focus on the latter format but the model can be generalized to other response formats.

The example in Figure 1A describes the sampling process for characteristics with only two levels, but the process can be extended to several levels. Consider a population that includes blue, purple, red, and pink voters. Figure 1B displays the process by which a red person would arrive at an answer about the percentage of voters in each level. As before, we assume some homophily in social environments. As a result, a red person has more red voters in her memorized social circle than there are in the general population (compare the population and social circle columns in Figure 1B). She also has in memory a few more of the voters from the neighboring, similar parties (purple and pink) than there are in the general population. Using the same similarity parameter $\rho = .9$ as before, her sample includes fewer red voters than her overall social circle (the sample columns in Figure 1B). Finally, to arrive at an answer (the population estimate columns in Figure 1B), we assume that she activates characteristics of her sample starting from the level with the highest frequency (typically this is also one's own level; here: red voters), with recall probability $\alpha = .9$ as before. She does this for all but the last level, which simply receives "the rest" of the sample, that is, all instances that have not yet been activated by other levels of the characteristic.

Taken together, the examples in Figure 1 demonstrate two qualitative signature patterns of social judgments predicted by the SSM (Galesic et al., 2012; Galesic, Olsson, & Rieskamp, 2013). First, the interplay of homophily and sampling processes leads to population estimates that look like smoothed versions of the social circle. For example, comparing the last and the second set of columns in Figure 1B, one can see that relative to social circles, population estimates are expected to be higher for rare characteristics in the social circle and lower for frequent characteristics. Second, the interplay of order of answering and memory activation leads to underestimation of the frequency of the category one answers about first (typically the largest category or the category one is explicitly asked about). For example, if people are asked about the frequency of red voters in the general population, they might fail to recall all such instances in their sample and their answer might include fewer red voters than they actually have in their samples.

Relationship to Previous Work

Other Social Judgment Models of Group Characteristics

Models of social judgment come in many flavors and styles. Here we relate the SSM to those models that describe how people make estimates of group characteristics, that is, how they judge relative or absolute frequencies of different characteristics in a particular group.[2] Such models are often inspired by exemplar models of categorization (e.g., Linville et al., 1989), sampling approaches to cognition (e.g., Pachur, Hertwig, & Rieskamp, 2013; A. M. Wood, Brown, & Maltby, 2012), range frequency theory (e.g., G. D. A. Brown, Wood, Ogden, & Maltby, 2015; Parducci, 1965, 1995; R. H. Smith, Diener, & Wedell, 1989), Brunswikian approaches to cognition (Fiedler, 1996), connectionist models (e.g., Kunda & Thagard, 1996; Van Rooy, Van Overwalle, Vanhoomissen, Labiouse, & French, 2003), or agent-based models (e.g., E. R. Smith & Collins, 2009; E. R. Smith & Conrey, 2007). We highlight four crucial dimensions on which social judgment models of group characteristics can be compared: (a) the assumed *environmental structure*, (b) *cognitive constraints*, (c) the type of *sampling processes*, and (d) the *form of the resulting judgments*. For each dimension we give examples of the most prominent models and describe how they relate to SSM.

Environmental structure. Only a few models explicitly represent different aspects of the environment. The exemplar model PDIST (Linville et al., 1989) assumes that people form perceived distributions of characteristics of exemplars currently activated in memory, enabling the model to handle different shapes of frequency distributions. Similarly, in the social judgment applications

[2] This focus on group characteristics means that we leave out social judgment models that only make predictions about characteristics of individuals (e.g., the exemplar-based model in E. R. Smith & Zarate, 1992).

of Decision by Sampling (Stewart, Chater, & Brown, 2006; A. M. Wood et al., 2012), range frequency models (G. D. A. Brown et al., 2015; R. H. Smith et al., 1989), and the social-circle heuristic (Pachur et al., 2013), differently shaped frequency and spatial distributions in people's environments can produce different valuations of a variety of attributes. In the BIAS model (Fiedler, 1996), environmental structure is represented in a noisy stimulus matrix with the columns representing stimuli and the rows representing probabilistic cues. Similarly to exemplar and sampling models, the SSM represents environmental structure in memory as frequency distributions of a person's immediate social environment.

Cognitive constraints. Cognitive constraints have been implemented in several different ways in models of social judgment of group characteristics. In exemplar models, they usually entail forgetting and retrieval parameters (Linville et al., 1989). The naïve intuitive statistician view assumes that people tend to correctly perceive and use the information in a given sample, but assume that the information provided in the sample can be used directly to estimate population properties (Juslin et al., 2007). Similarly to the exemplar approach, in the SSM we implement memory and activation constraints in the form of the recall probability parameter α and the similarity parameter ρ. In contrast to the assumption of naïve use of sample information where individuals do not correct their sample-based impressions, the SSM assumes, in line with previous empirical results (Galesic et al., 2012), that people do not naively use their social circle knowledge but adjust it to make it more suitable for judgments of groups outside of their social circle.

Sampling processes. Different models assume different sampling processes, but most follow some version of exemplar-based processes in which exemplars are retrieved from memory, or from the immediate environment, based on their similarity to the probe that has to be judged. Some models also postulate explicit search rules within different circles of one's social network (Pachur et al., 2013). In the SSM, the activation process is also governed by similarity, but with a more specific activation process where instances get activated by the reference class specified by the question and whether the instance has the target characteristic.

Resulting judgments. Different models focus on different types of judgments or decisions: conditional probabilities and contingency judgments (Fiedler, 1996), binary pairwise comparisons and absolute frequencies (Pachur et al., 2013), relative ranks and corresponding valuations (e.g., A. M. Wood et al., 2012), and frequency distributions (Linville et al., 1989). The SSM can produce single probability judgments *and* relative ranks *and* estimates of frequency distributions.

In sum, a major novel contribution of the SSM is that it simultaneously incorporates an interaction between the structure of the social and task environments and the cognitive processes, produces quantitative predictions of different types of frequency judgments, and explains several judgment effects in social cognition. None of the reviewed models besides the SSM achieves that.

Comparison With Statistical Accounts of Social Judgments

Several previous accounts of social judgments have focused solely on statistical mechanisms such as noise asymmetries and scale attenuation (Harris & Hahn, 2011; Hilbert, 2012). In our own past work, we implemented a statistical mechanism in a model which assumed that judgments of characteristics of broader environments were based on "smoothed" versions of distributions of these characteristics in one's social circle (Galesic et al., 2012). A single parameter controlled the amount of "smoothing" which moved all estimates toward the average of the social circle distributions. However, this model did not specify the processes that produced "smoothed" estimates and consequently could not explain all of the empirically observed data patterns. Specifically, the model could not predict a relatively rare but consistently appearing pattern of estimates, whereby participants judged the category that was most frequent in their social circle as even more frequent in the general population. For example, in a study of Galesic et al. (2012; see description of Study 1 in Appendix A) such a pattern of estimates appeared for 2% to 8% of participants, depending on the characteristic. Overall, 41% of participants showed such a pattern of population estimates for at least one characteristic. Unlike that statistical model, the SSM, described in the present paper, specifies cognitive processes underlying social judgments and can predict this pattern whenever the largest category in one's social circle is not one's own category. This occurred in most (79%) of the cases in which such a pattern was found in Study 1. Of these cases, the SSM predicted such a pattern for on average 43% of them (from 31% to 53%, depending on the characteristic), while our previous model predicted 0% of such cases.

Furthermore, the previous statistical model could not predict the finding, also noted in Study 1 described here, that participants occasionally assigned a very low frequency (close or equal to 0%) to some categories in the general population. Such estimates were given by 4% to 32% of participants, depending on the characteristic. The new SSM predicted 69% to 87% of such cases (on average 76% across all 10 characteristics), while the previous model predicted 0% of these cases. The new SSM predicted some but not all cases in which these patterns occurred, showing a constraint of the model. This illustrates that the model is not overly flexible and able to predict any pattern of results (see also the sensitivity analysis in supplementary online material 1 for further checks).

Methodological Limitations of Studies of Social Judgments

To understand reliable effects in social cognition, it is necessary to take a closer look at how people represent and make judgments about their social environments and how the properties of their environments influence their judgments. The way social judgments are usually studied might, however, prevent a detailed analysis of the interplay between mind and environment. Specifically, four limitations are shared by many studies of social judgment. First, participants are often not explicitly told which reference class they have to assess—their peers, family and friends, or the general population. Instead, they are often instructed to make judgments about life circumstances of vaguely specified "other people" or compare themselves to an "average person" (for an exception see, e.g., Epley & Dunning, 2006). Second, the accuracy of their assessments is frequently assessed by comparing the assessments to benchmarks obtained from nonrepresentative samples, rather than from representative samples of the relevant reference class.

For instance, people's estimates of "average student" are compared to estimates obtained from a sample of students taking psychology courses. Third, when indirect estimates are used, participants are typically asked to assess only a summary indicator of a distribution (usually average), rather than the whole distribution (for an exception, see Study 2 in Alicke, Klotz, Breitenbecher, Yurak, & Vredenburg, 1995). Fourth, conventional measures of bias used in studies where participants' self-judgments are compared with the same participants' estimates of "average" others overestimate the amount of bias (Heck & Krueger, 2015). For example, one traditional measure of self-enhancement conflates hits with false alarms, which leads to an overestimation of self-enhancement. If a participant's estimate of the number of questions that she answered correctly is larger than her estimate of the number of questions that an average person answered correctly, the person is traditionally considered a self-enhancer. But that answer could be either a "hit" (the person answered more questions correctly) or a "false alarm" (the person did not answer more questions correctly; Study 2 in Heck & Krueger, 2015; see also Epley & Dunning, 2006, and Moore & Small, 2007).

A notable exception that avoided most of these limitations is the study of Nisbett and Kunda (1985). In that study, students assessed the whole distributions of various life circumstances of their peers, and their answers were compared with the actual values obtained from a representative student sample. Following the lead of Nisbett and Kunda (1985), in all studies described in this article we used explicit reference classes (e.g., well-defined social circles, or the general population of one's country),[3] benchmarks representative of the relevant reference class (e.g., national probabilistic sample estimates of characteristics in the general population), and distributional questions about frequency of different properties of people's social environments, rather than only single summary indicators. The distributional questions were either about populations (e.g., "What percentages of adults living in the Netherlands fall into the following categories?") or social circles (e.g., "What percentages of your social contacts fall into the following categories?"). We also circumvent the problems of traditional measures of bias by explicitly comparing the estimated and the actual percentage of people that are positioned above or below an individual's own position. In all empirical studies reported here, 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."[4]

Testing the SSM's Assumptions

Do People Disregard Those Who are Most Similar to Themselves?

A key cognitive assumption in the SSM is that people are able to disregard the instances in memory most similar to themselves, leaving the remaining instances to be used as a sample on which to base their population estimates. This appears to be at odds with the literature that suggests that people have problems disregarding information about themselves when judging others (e.g., Dunning & Hayes, 1996; Kruger, 1999; Weinstein, 1980; Weinstein & Lachendro, 1982). To investigate whether people indeed disregard similar instances, we examine the differences between individuals' estimates of the prevalence of different categories in their social circles and in the general population. If they are able to disregard similar instances when making population estimates, we would expect a negative difference between social circle and population estimates for their own category and positive differences for more distant categories. For example, if a person has low income, we would expect that this person has relatively large proportion of low income people in her social circle, but that she estimates that the proportion of low income people in the general population is lower than in her social circle. Results of this analysis are shown in Figure 2 and in supplementary online material 2.

Figure 2 shows the difference between individuals' population estimates and their social circle estimates for 10 characteristics studied in Galesic et al. (2012) who asked a national sample of the Dutch population to report population and social circle estimates of distributions for 10 different characteristics (see Study 1 in Appendix A). The differences between individuals' population estimates and their social circle estimates are displayed for the category of which the individual is a member (i.e., their own category, denoted with a 0 on the *x*-axis) and the categories of which the individual is not a member (negative or positive numbers on the *x*-axis). Note that for some characteristics the number of observations in extreme categories was very low, as reflected in large standard errors. Nevertheless, the average difference across characteristics is indeed negative in the individuals' own category, and positive in most distant categories. This is in line with the key SSM assumption that people disregard instances similar to themselves when using their social circles to make population estimates. The same pattern of results was replicated in two further studies (see supplementary online material 2).

Are Social Circle Reports Valid?

The social sampling model suggests that people have good knowledge of their immediate social circles and that biases occur when they are asked to give estimates about broader social environments that are not well represented in their memory. Evidence for this assumption was found by Galesic et al. (2012; Study 1 in Appendix A). The average of social circle distributions reported by participants corresponded closely to the true population distributions, suggesting that participants' social circle reports were unbiased (see supplementary online material 3, Figure S3A). In contrast, participants' population estimates showed systematic deviations (Figure S3A, also see section Explaining Self-Enhancement and Self-Depreciation). Median correlations between true population distributions and average social circle distributions were higher, and root mean square deviations lower (r = .87 and $RMSD$ = 4.9) than those between true population distri-

[3] Some studies of social judgments used questions about an "average person" or "others" (recent examples include J. D. Brown, 2012; Wojcik & Ditto, 2014). It is an open question whether in everyday judgments people mostly assess vaguely defined "others" or base their judgments on distributional representations.

[4] In further studies we found that the definition of social contacts can be modified for the purpose of a particular study and still produce useful results. For instance, in a study by Galesic et al. (2018) investigating voting behavior, we asked for all contacts the participants have communicated with in the last month, either face-to-face or otherwise.

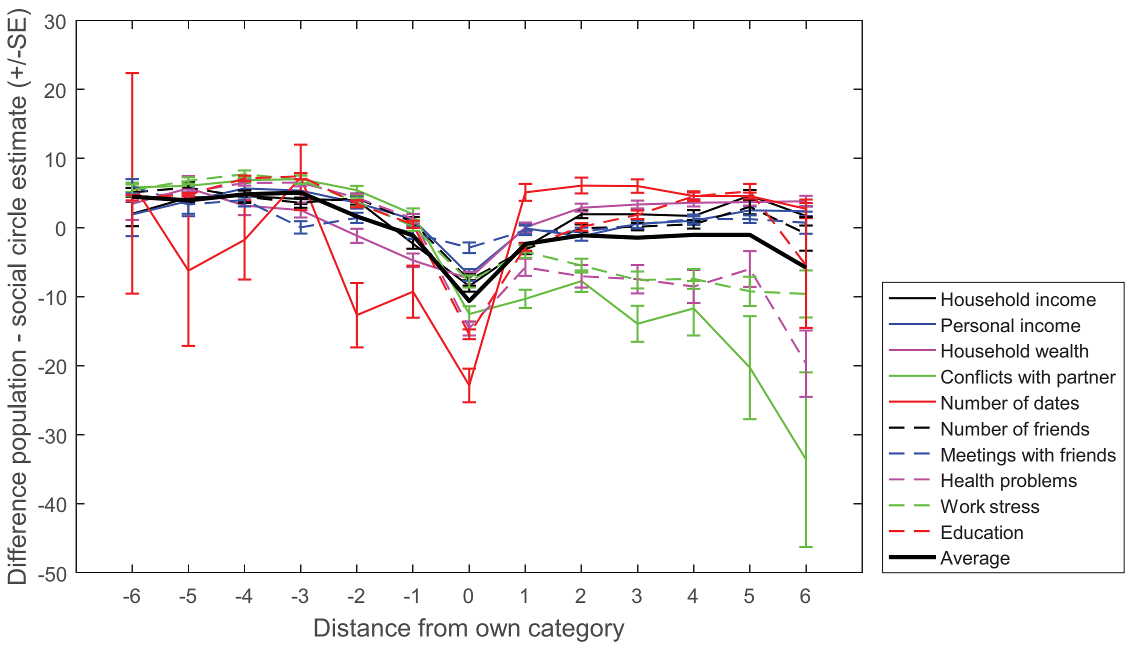

Figure 2. Difference between population and social circle estimates, for categories that are at different distances from one's own category, for the 10 characteristics in Study 1. The numbers on the *x*-axis represent the differences between own category and the other categories. The thick black line is the average over the characteristics and the error bars represent standard errors. As predicted by the SSM, the average difference across characteristics is lower in own category than in other categories. See the online article for the color version of this figure.

butions and average population estimates (r = .57, *RMSD* = 8.9, respectively).

To further investigate these differences, we calculated three sets of means and standard deviations for each of the 10 characteristics: for the true population distributions, population estimates, and social circle distributions (see supplementary online material 4). As would be expected if the reports of social circles were relatively accurate and unbiased, we found that the true population means and social circle means typically corresponded quite well (*RMSD* ranged from 2.5 to 6.1). In contrast, means of population estimates were further away from the true population means for nine of the 10 characteristics compared to the social circle estimates, suggesting some systematic biases (*RMSD* ranged from 4.4 to 18.1). In addition, as expected because of homophily, average standard deviations of participants' social circles were much lower than the true population standard deviations. Standard deviations of participants' population estimates were closer to the true population but still underestimated, a finding that echoes the literature on perceived homogeneity of outgroups (e.g., Judd, Ryan, & Park, 1991). Taken together, these findings suggest that people's social circle reports are indeed quite valid indicators of the actual properties of their immediate social environments.

Are Social Circle Reports Reliable?

To answer this question, we asked n = 152 participants (see Study 2 in Appendix A) to complete the same questions about their social circle distributions twice, a week apart. Median test–retest correlations were high, ranging from r = .68 for income of their social circles to .85 for their political orientation, .87 for level of stress, .91 for their voting behavior (i.e., for which of nine different parties will their contacts most likely vote, if at all, in the then upcoming German parliamentary elections), and .92 for education. We also investigated participants' estimates of the size of their social circles across three waves, each a week apart. These estimates were also reliable, with an average test–retest correlation of r = .83.

Are Social Circles Used to Produce Population Estimates?

If people use their social circles as a basis for their judgments of population distributions, differences in individual social circles should be reflected in people's population estimates. Specifically, people who have larger social circles, and social circles that are more representative of the overall population, should give more accurate population estimates than people who have social circles that are smaller and less representative of the general population. Indeed, Figure 3A shows a positive relationship between social circle size on the one hand and the average correlation between people's population estimates of nine different characteristics and the true population distributions on the other (r = .19; Study 1). Figure 3B shows, as expected, a negative relationship between social circle size and the average deviations (*RMSD* between estimated and true population distributions (r = −.13). These relationships point to the expected direction, although they are relatively weak as larger social circles are not necessarily more representative. We therefore also compared more direct measures of representativeness with accuracy of population estimates. Figure 3C shows a positive relationship (r = .30) between the repre-

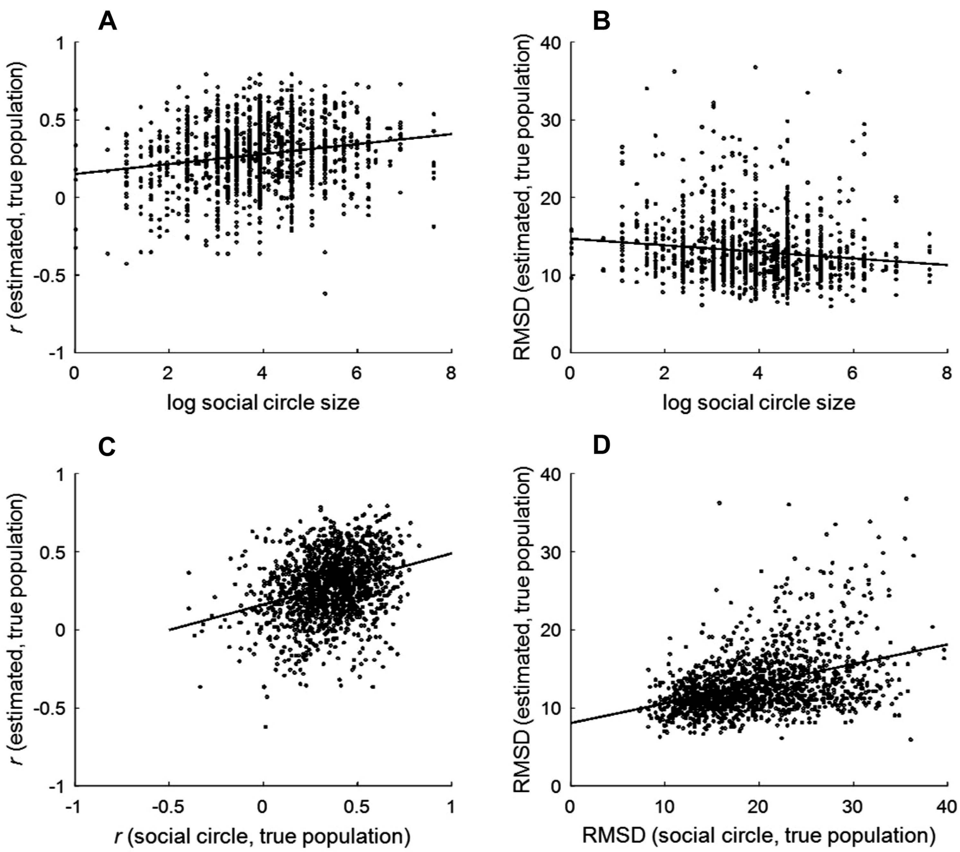

Figure 3. Accuracy of population estimates (*y* axes) is related to the size of individual social circles (*x* axes in A and B) and their representativeness for the general population (*x* axes in C and D). (A, C) Accuracy in terms of correlations with true population distributions. (B, D) Accuracy in terms of root mean square deviation (*RMSD*) from true population distributions. Each point represents one person from Study 1.

sentativeness of the social circle, measured as the correlation of social circle distributions and true population distributions, and the correlation between population estimates and true population distributions. Figure 3D shows a positive relationship between deviations of participants' social circle distributions from true population distributions on the one hand and deviations of their population estimates from true population distributions on the other (r = .39). All of the relationships shown in Figure 3 suggest that social circles are indeed used to make population estimates.

In What Order do People Answer Distribution Questions?

When the sampling process involves characteristics with more than one level, the SSM assumes that people start with the largest category or their own category and proceed toward the smallest category (see example in Figure 1B). To test this assumption, we collected "paradata" (Kaczmirek, 2014; Kreuter, 2013) consisting of all clicks and keystrokes participants made while responding to questions about social circle and population distributions (n = 152, see description of Study 2 in Appendix A). To avoid systematic biases due to the custom of reading and writing from left to right in the populations we studied, we rotated the order of response options (with lowest on the left and highest on the right, and vice versa) across participants. Figure 4 shows the dominant strategy participants followed when answering questions regarding the distributions for six different characteristics (income, political orientation, level of stress, education, voting behavior of their social circle, and voting behavior in the general population). Each characteristic had from five (stress) to 10 (voting behavior) response categories. Figure 4 shows that most participants started answering for the largest population category (36%) although almost as many started with the left-most category. Importantly for the SSM, most gave their last answer for the smallest population category (63%).

Explaining False Consensus and False Uniqueness

The *false consensus effect* (Ross, Greene, & House, 1977) or "looking glass perception" (Fields & Schuman, 1976) or more generally social projection (Krueger, 1998, 2000, 2007; Krueger & Clement, 1994, 1997; Robbins & Krueger, 2005) describes a phenomenon that people who exhibit a certain behavior or endorse a particular opinion believe that this behavior or opinion is more common overall than do people with different behaviors or opinions. For example, Democrats would judge that democratic views

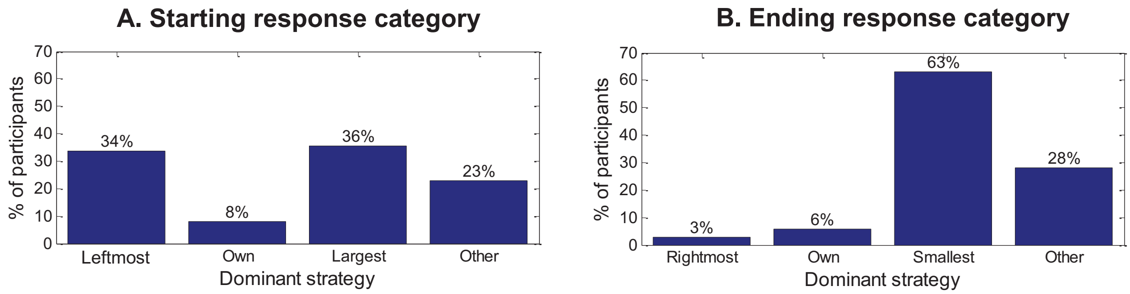

Figure 4. When answering distribution questions in Study 2, most participants started with the largest category (A) and ended with the smallest category (B) as predicted by the social sampling model. See the online article for the color version of this figure.

are more widespread in the general public than Republicans would. This kind of result has been documented so often that the false consensus effect has been considered an automatic response that may be "developmental vestiges of the infantile belief that all others are like us" (Krueger & Clement, 1994, p. 609). However, an opposite effect called *false uniqueness* has also been documented (Frable, 1993; Mullen, Dovidio, Johnson, & Copper, 1992). People holding a particular view sometimes tend to think that their view is less popular than do people holding a different view.

At least five different explanations have been proposed to explain false consensus (Marks & Miller, 1987). First, people are likely to have selective exposure to similar others, so their estimates of larger social environments are based on biased samples. Second, their preferred view may be more salient to them than a different view, which may make them think that their preferred view has stronger social support. Third, people may believe that situational factors that led them to hold a particular view will affect others in a similar way, leading them to adopt the same view as well. Fourth, believing that others share one's view may have a motivational cause, such as fulfilling the need to validate one's own belief and maintain self-esteem. Fifth, false consensus is in line with a Bayesian analysis that assumes a uniform prior distribution and one's own view as the only evidence (Dawes & Mulford, 1996).

However, none of these accounts can simultaneously explain false consensus *and* false uniqueness without further assumptions. Suls and Wan (1987) extended the motivational account and proposed that false uniqueness can contribute to one's self-esteem when the behavior or view in question is desirable, but they found inconsistent support for this view (Suls, Wan, & Sanders, 1988). Moore and Kim (2003) showed that because people rely more on information about themselves than about others when forming a judgment of the prevalence of their views, effects similar to both false consensus and false uniqueness can occur. However, their measure of these effects was different from that used in most other studies of false consensus (Mullen et al., 1985): They used the difference between people's judgments and true population values rather than the difference between judgments of groups of people holding different views, the latter being the standard way of measuring false consensus. We argue that false consensus and false uniqueness can both occur, depending on the homophily of people's social environments and, additionally, on the format of questions used to elicit social judgments. Furthermore, we show how the SSM can provide a parsimonious explanation for both effects.

Model Predictions: Effects of Homophily

The SSM predicts that the homophily of one's social circle affects whether false consensus or false uniqueness will appear. Figure 5 illustrates the SSM's predictions for a hypothetical example where red (left panels) and blue (right panels) individuals are asked to predict the percentage of red people in the population. The top panels (Figure 5A) assume stronger homophily, or the tendency of people of the same color to group together. Here, while the percentage of red people in the population is 60%, a red person encounters 72% and a blue person only 42% red people in the environment (these estimates were computed assuming a Coleman Index of homophily of .3). Assuming that the parameters of the SSM are $\alpha = \rho = .9$ for both individuals, red's estimate of the percentage of red people in the population is higher than blue's estimate (62% vs. 42%). This difference resembles the false consensus effect.

For the bottom panels (Figure 5B) weaker homophily is assumed: A red person still encounters more red people than there are in the general population, 63%, but the difference between the percentage of red people in the population (60%) and in red's social circle is smaller than before. Similarly, a blue person still encounters fewer red people than there are in the general population, 56%, but the difference from the population value is again smaller than before. These values correspond to a Coleman Index of .08. Here, assuming the same parameters as before, $\alpha = \rho = .9$, red's estimate of the percentage of red people in the population is now lower than blue's estimate (53% vs. 56%). This difference resembles the false uniqueness effect.

In sum, the SSM predicts that the same cognitive processes can lead to false consensus when social circles are characterized by strong homophily and to false uniqueness when social circles have weak homophily, holding both α and ρ constant. Level of homophily can depend both on the specifics of a social environment and on a particular characteristic. For instance, some neighborhoods might be relatively more isolated from the broader society because of various structural constraints, either physical (e.g., limited transportation options, distance) or social (e.g., internally or externally imposed norms against socialization with other groups). In addi-

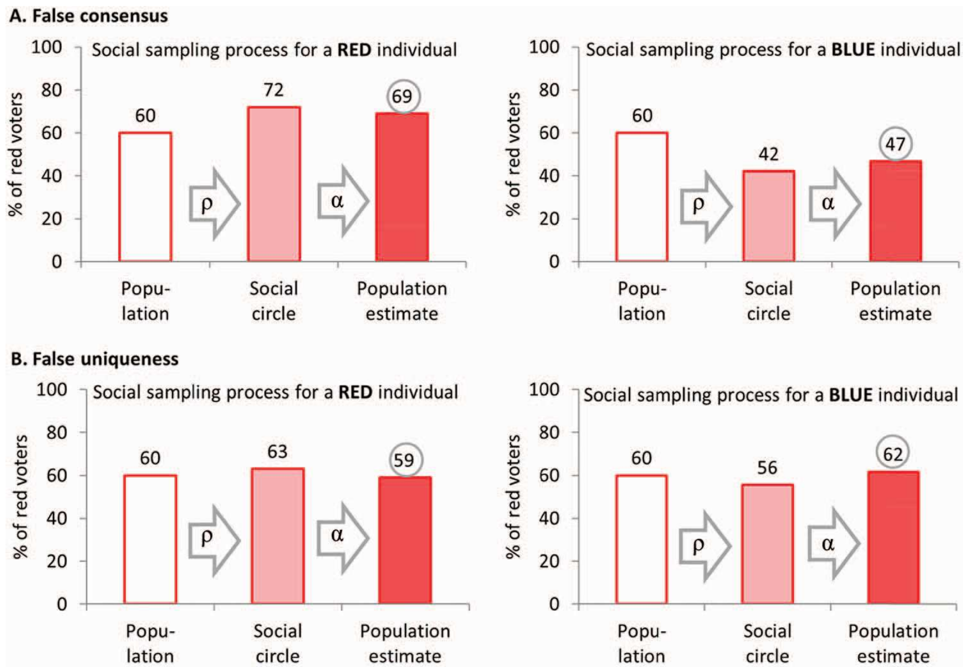

Figure 5. Social sampling model predictions of false consensus and false uniqueness effects, assuming α = ρ = .9 in all four panels. (A) False consensus occurs when social environment has high homophily (Coleman Index = .30). (B) False uniqueness occurs when social environment has low homophily (Coleman Index = .08). See the online article for the color version of this figure.

tion, some characteristics can be more conducive to homophily than others. Income, race, and education are some examples, but many other beliefs and behaviors can also be more likely to occur in some social circles than in others (Christakis & Fowler, 2007, 2008; Rosenquist, Murabito, Fowler, & Christakis, 2010).

Testing Model Predictions for Effects of Homophily

Procedure. We asked 50 participants from the United States and 50 from Germany whether they themselves exhibit 10 different characteristics. Each question had two possible responses (yes or no; see Appendix A for details on Study 3, including full text of questions). Thereafter, they estimated the prevalence of people who exhibit those beliefs and behaviors ("performers") in their social circle and the general population.

Empirically obtained effects. In the United States (Germany), six (two) of 10 characteristics showed false consensus, and four (eight) false uniqueness. To explore the prediction of the SSM that the size of false consensus is affected by homophily in individual social circles in respect to a given characteristic, we calculated the Coleman Index of homophily for each characteristic (in this case equal to the difference between percentage of performers in the social circle of the performers and the percentage of performers in an average social circle, divided by the percentage of nonperformers in an average social circle; Coleman, 1958; Signorile & O'Shea, 1965) and compared it with the size of false consensus (or false uniqueness) obtained for that characteristic. As Figure 6 shows, while different characteristics have different levels of homophily in the U.S. and German studies, in both countries there is a positive relationship between homophily and the size of false consensus effects (the correlation is .50 in the United States and .61 in Germany).

Predicted effects. In each country, we predicted individual participants' estimates of the percentage of performers in the population using the SSM estimated in the same way as for the distribution estimates (average parameter values: United States, $\alpha = .86$ and $\rho = .77$; Germany, $\alpha = .87$ and $\rho = .81$). Figure 7 shows that such rough predictions were still able to capture correctly the main patterns in the data, namely, which characteristics exhibit false consensus, and which false uniqueness.

Model Predictions: Effects of Response Format

The way social judgments are elicited is another important factor that might lead to both false consensus and false uniqueness effects for the very same characteristics, even when the level of homophily in the environment is fixed. Specifically, the questions that are used to ask about social judgments can have different response formats. Most studies investigating false consensus use one of two response formats. They may ask about the estimated percentages of both those people who exhibit a certain behavior or endorse a particular view ("performers") and those who do not ("nonperformers"). For example, "What % of your peers do you estimate would agree to carry the sandwich board around campus?__% What % would refuse to carry it?__% (Total should be 100%)" (Ross et al., 1977, p. 290). Or they may ask only about the percentages of performers, for example, "What percentage of students do you think agreed to wear the sign?" (Krueger & Clement, 1994, p. 605). It is well known from the

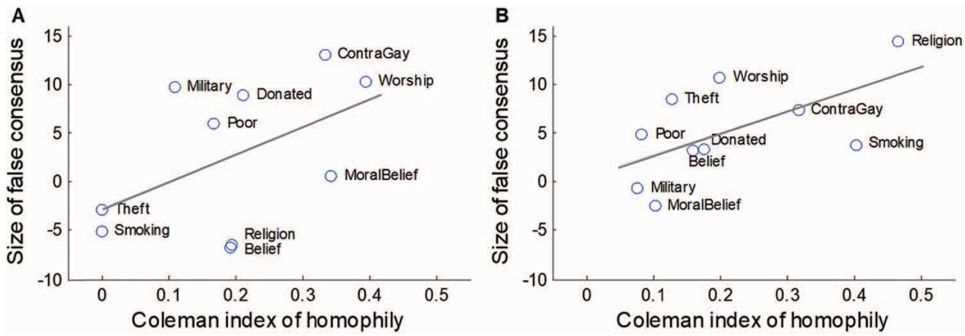

Figure 6. Relationship between homophily and size of false consensus. Data are from U.S. participants (A) and German participants (B) in Study 3. See the online article for the color version of this figure.

survey methodology literature that response formats can have strong effects on people's answers (Tourangeau et al., 2000). Similarly, research on subjective probability calibration shows that people can appear overconfident, well calibrated, or underconfident depending on the response format used (Juslin, Wennerholm, & Olsson, 1999).

In SSM, response formats are predicted to influence judgments through the process of memory activation: Given that parameter α is almost always smaller than its maximum value of 1, people will underestimate the prevalence of the category they are asked about even if their sample perfectly reflects the population. For example, when one is asked about the percentage of red people in the population, their estimate is predicted to be lower than the proportion of red people in their samples (see Figure 5). If they are not explicitly asked about the other category and instead their answer is inferred by deducting their estimate for the first category from 100%, then the prevalence of the alternative category will be overestimated.

This leads to the following specific predictions of the SSM (shown in detail in Figure 8). First, false consensus will be largest if performers are asked about nonperformers (which will inflate their estimate of performers) and nonperformers about performers (which will inflate their estimate of nonperformers). Second, false uniqueness will be largest in the opposite case, when performers are asked about performers and nonperformers about nonperformers. Third, the standard way of asking questions in false-consensus studies, by asking both performers and nonperformers about performers or about both groups, should produce no bias in the absence of further assumptions about sampling processes and homophily, suggesting that question formats used in previous studies were well chosen as baseline measures of false-consensus effects.

The SSM predictions suggest that false consensus is not a robust effect, because it can be manipulated to become false uniqueness just by the way questions are asked. Figure 8 shows predictions of the SSM for the average size of the false-consensus effect across 10 different fictitious characteristics with population prevalence ranging from 1% to 91% in steps of 10 percentage points. The figure shows the effects across nine different response formats. The first part of each label denotes the response format assigned to performers (abbreviation before a comma), and the second to nonperformers (abbreviation after a comma). Furthermore, P means that participants are asked about performers; PN means that participants are asked about both performers and nonperformers; and N means that participants are asked about nonperformers. For instance, the label "N,P" means that performers are asked to

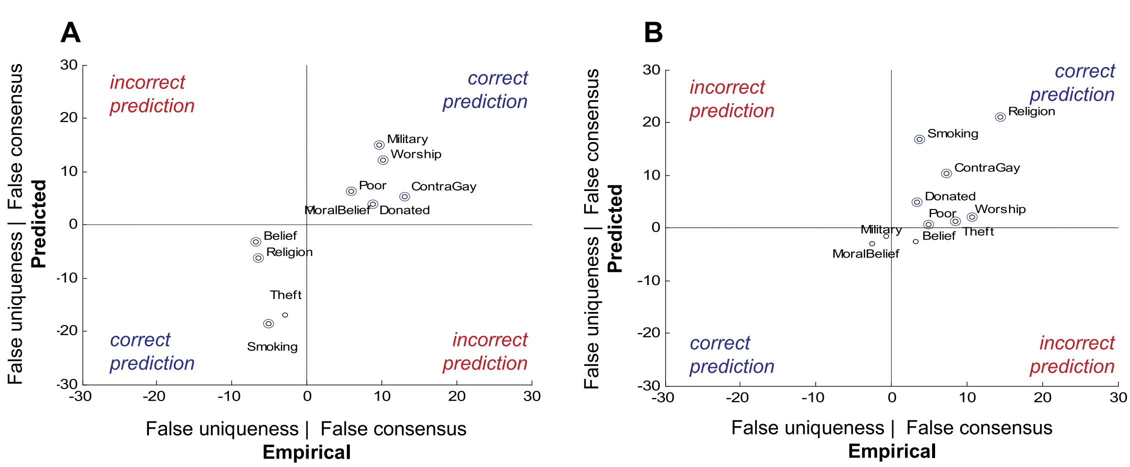

Figure 7. Predicted patterns of false consensus for different characteristics. Data are from U.S. participants (A) and German participants (B) in Study 3. Double circles denote empirical false consensus or uniqueness effects that were of at least moderate size (Cohen's $d \geq 0.2$). See the online article for the color version of this figure.

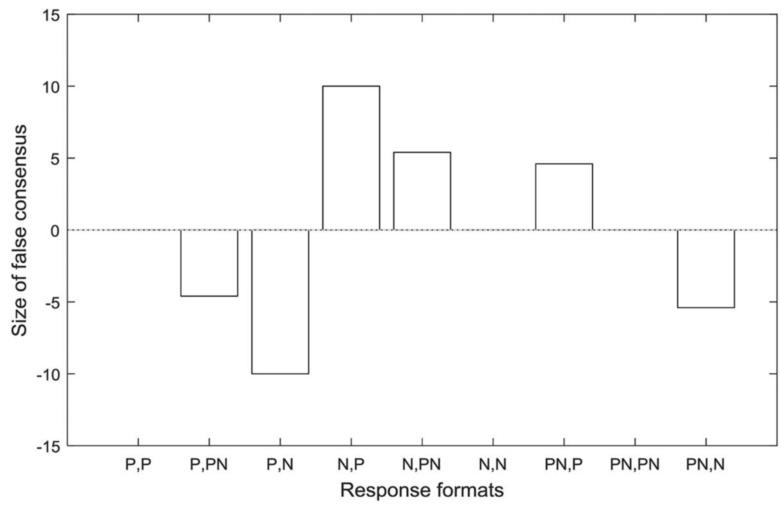

Figure 8. Theoretical predictions of the size of false-consensus effects, depending on response formats, obtained by applying the social sampling model (SSM) to fictitious data (see text for more details). Labels on the *x*-axis: the first part of each label denotes the response format assigned to performers (abbreviation before a comma), and the second to nonperformers (abbreviation after a comma). P = asked about performers; PN = asked about both performers and nonperformers; N = asked about nonperformers. For instance, the label "N,P" means that performers are asked to estimate the percentage of nonperformers, and vice versa; "PN,PN" means that both performers and nonperformers are asked to estimate both percentages. Because memory activation affects categories one is asked about, the SSM predicts that false consensus will be highest when performers are asked about nonperformers and nonperformers about performers ("N,P") and lowest (resembling false uniqueness) when performers are asked about performers and nonperformers about nonperformers ("P,N").

estimate the percentage of nonperformers, and nonperformers about performers; "PN,PN" means that both performers and nonperformers are asked to estimate both performers and nonperformers. To be able to observe effects of response formats without other influencing factors, in this example we assume that there is no homophily in the environment—prevalence of performers is the same in social circles of performers and nonperformers. Furthermore, we assume almost perfect recall, $\alpha = .9$, and that population estimates are based on the whole social circle, without sampling according to the similarity of instances to the population ($\rho = 1$; reducing ρ does not change the shape of the curve). As can be seen, even without assuming any homophily in the environment, this simplified model predicts both false-consensus and false-uniqueness effects for the same characteristics, depending only on how the questions were asked (see Figure 8).

Testing Model Predictions for Effects of Response Format

Procedure. We use data from $n = 104$ U.S. participants who answered questions about 10 of their own characteristics, for instance smoking, donating to charity, and believing in a god, and were consequently classified as either performers or nonperformers of a particular characteristic (see Study 4 in Appendix A for more details). Participants furthermore estimated the percentage of performers and/or nonperformers in their social circle and in the general population of the United States. For each characteristic, a random third of performers and a random third of nonperformers gave estimates of social circle and population percentages in one of the following response formats: (a) estimating *only* the percentage of performers, (b) estimating *only* the percentage of nonperformers, and (c) estimating *both* the percentage of performers and the percentage of nonperformers.

Empirically obtained and predicted false-consensus effects. Figure 9 shows both the empirically obtained false-consensus effect for each characteristic (numbers) and on average (solid-lined bars), as well as predictions of the SSM (dashed-lined bars). The parameters were estimated using the same procedure as before. The average parameter values were $\alpha = .90$ and $\rho = .80$. Note that compared with Figure 8, all predictions are shifted toward more positive values, reflecting homophily in real-world social environments. The SSM predicts the empirical patterns reasonably well, in particular the phenomenon (demonstrated previously in a fictitious example in Figure 8) that false consensus is lowest for response format "P,N" (performers reporting about performers and nonperformers about nonperformers) and highest for response format "NP" (vice versa).

Explaining Self-Enhancement and Self-Depreciation

Decades of research on social comparison (Festinger, 1954) seems to show that people's perceptions of how they measure up against others are imperfect. People appear to think they have better traits, abilities, and future prospects than other people do, or that their position relative to that of others is better than it actually is (Loughnan et al., 2011; Sedikides, Gaertner, & Toguchi, 2003; J. V. Wood, 1989). Self-enhancement effects such as the better-than-average and optimism biases have been documented for characteristics as diverse as driving ability, friendliness, intelligence, and future prospects and are considered to be among the most

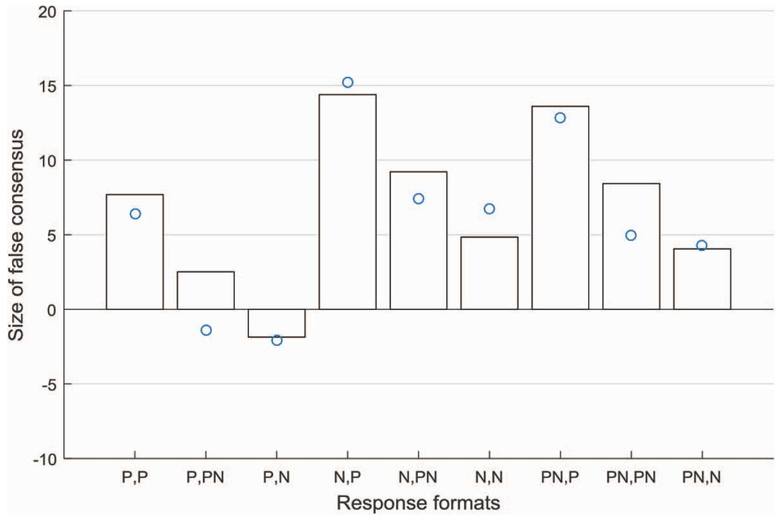

Figure 9. Average empirically obtained estimates of false consensus (bars), and their social sampling model predictions (circles). Labels on the *x*-axis: the first part of each label denotes the response format assigned to performers (abbreviation before a comma), and the second to nonperformers (abbreviation after a comma). P = asked about performers; PN = asked about both performers and nonperformers; N = asked about nonperformers. For instance, the label "N,P" means that performers are asked to estimate the percentage of nonperformers, and vice versa; "PN,PN" means that both performers and nonperformers are asked to estimate both percentages. See the online article for the color version of this figure.

robust findings in the literature on social comparison (e.g., Alicke & Govorun, 2005; Chambers & Windschitl, 2004; Roese & Olson, 2007). However, robust findings of the opposite effect have also been documented, namely, of self-depreciation (Kruger, 1999), in particular for people who otherwise show superior skills (Burson, Larrick, & Klayman, 2006; Moore & Small, 2007). Most accounts of self-enhancement cannot explain self-depreciation. One such account is a *motivational bias*: People distort reality to improve their sense of self-esteem and well-being (Alicke et al., 1995). Another is *cognitive incompetence* of people who overestimate their social position (Kruger & Dunning, 1999).

Two existing types of accounts can explain both self-enhancement and self-depreciation. One type includes different *egocentric accounts* of social judgments (Krueger, 2000, 2007). Prominent examples are two-stage models of social judgment where people are assumed to use self as an anchor and a primary source of information about others and fail to adequately correct their judgments with additional information about others (Epley, Keysar, Van Boven, & Gilovich, 2004; Kruger, 1999). This leads to an egocentric bias which can produce self-enhancement effects for tasks that are easy for most of those other people and self-depreciation for tasks that are difficult (Kruger, 1999). This argument echoes the proposal that in absence of other information it is Bayesian rational to rely on own characteristics when judging others, as in most social environments one will be in majority (Dawes, 1989; Dawes & Mulford, 1996). In a similar vein, Moore and Small (2007) proposed that asymmetries in judgments of self and others stem from people having more information about themselves than about others and can produce effects similar to self-enhancement and self-depreciation. Nisbett and Kunda (1985) have also suggested that social judgments include an egocentric component, along with actual information about others and general sense about overall population properties. However, none of the egocentric accounts currently provides a computational model that would explain how people produce complete frequency distributions of characteristics of others, because they assume that people make social judgments based just on their own position (but see Moore & Healy, 2008 for a similar account of overconfidence). Without the precise specification of the prior distribution that people have in their minds (e.g., whether they consider their social circles, the general population, or other priors such as a uniform or a symmetric distribution), it is not possible to predict whether the resulting effects will resemble self-enhancement or self-depreciation.

Another account can explain both how people form frequency distributions of different characteristics of their social environments, and how this process can produce self-enhancement and self-depreciation effects. It draws on 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 population but that their reports contain some random noise that leads to underestimation of high performance and overestimation of low performance. This is the only other account of self-enhancement and self-depreciation that can be precisely computationally specified and whose quantitative predictions can be compared with those of SSM (as we do in section An Alternative Account: Population Sampling Model). Note that the regression account in its pure form cannot explain the frequently observed finding that worse-off people (e.g., those with bad results on a task used in a particular study) make larger errors than better-off people (those with good results; e.g., Burson et al., 2006; Ehrlinger, Johnson, Banner, Dunning, & Kruger, 2008; Krueger & Mueller, 2002; Kruger & Dunning, 1999), as the extent of regression is assumed to be the same for both groups of people. Therefore, various systematic biases have been proposed that counteract or add to the regression effects, such as a general better-than-average bias (Krueger & Mueller, 2002) or a test-difficulty bias (Burson et al., 2006). The origins of these biases remain unclear and they appear to be redescriptions rather than explanations of the phenomena of self-enhancement and self-depreciation.

Model Predictions

The SSM makes two specific predictions about the expected patterns of social judgments, depending on the shape of the underlying frequency distribution in the general population and people's own position in that distribution. Together, these predictions explain the complete pattern of results observed in previous studies, namely, that both self-enhancement and self-depreciation effects have been observed, and that people who are worse off on a given characteristic tend to self-enhance more than people who are better off.

The *first prediction* is that average population estimates will appear as if they were affected by self-enhancement when the underlying distribution in the general population is J-right shaped and by self-depreciation when the underlying distribution is J-left shaped. This happens because of the interplay of the sampling processes (described in Figure 1) and the shape of the frequency distribution of a particular characteristic in the general population. Specifically, when many people are doing well (J-right-shaped distribution, given that levels of a characteristic are ordered from least to most positive), sampling processes (see Figure 1) will lead to underestimation of the frequency of successful people. This will make the position of an average participant appear better than it really is, leading to self-enhancement. Similarly, when most people are doing badly (J-left shaped), estimates of the frequency of successful people will be inflated for the same reason. This will make the position of an average participant appear worse than it really is.

The *second prediction* is that people who are worse off on a particular characteristic will show systematically different errors in their population estimates compared to people who are better off on that characteristic. The relative size of errors will depend on the underlying distribution shape and will sometimes resemble higher self-enhancement and sometimes lower self-depreciation of worse-off compared to better-off people. These effects will occur because of the interplay of homophily, distribution shapes, and sampling processes. Specifically, because of homophily reflected in people's social circles, everyone is expected to overestimate their part of the population distribution relative to the true distribution. For worse-off people this means overestimating the lower part of the population distribution. Consequently, their own estimated percentile will be overestimated relative to their true percentile. For better-off people, this means overestimating the upper part of the population distribution. Consequently, their own estimated percentile will be underestimated relative to the true percentile. When the population distribution is symmetric, this will result in self-enhancement for worse-off individuals and self-depreciation for better-off ones. When the population distribution is not symmetric, this basic pattern becomes an overall self-depreciation effect when the shape is J-left (with worse-off people self-depreciating less than the better-off ones) and self-enhancement effect when the shape is J-right (with worse-off people self-enhancing more than the better-off ones).

An Alternative Account: Population Sampling Model

As mentioned before, the SSM assumes that people base their judgments of broader populations only on representations of their immediate social environments, or their social circles. We compare the SSM predictions with a "population sampling model" or PSM, inspired by the regression account mentioned before. The PSM assumes that people have representations of the overall social environment, not only their own social circles. Like the SSM, the PSM makes the first prediction described before, but because it assumes that everyone has essentially the same instances of social environments in their memory, it cannot explain systematic individual differences following from the second prediction described in the previous paragraph.

The PSM is a reasonable benchmark model, as the assumption that well-adapted cognition should possess such broad representation is a frequent tacit assumption of previous accounts of social cognition effects. It is also an explicit assumption of different accounts suggesting that statistical regression is a contributing factor to a wide range of biases including unrealistic optimism, overplacement, and overconfidence (e.g., Erev, Wallsten, & Budescu, 1994; Fiedler, Unkelbach, & Freytag, 2009; Harris & Hahn, 2011; Hilbert, 2012; Juslin, Winman, & Olsson, 2000; Moore & Healy, 2008). For example, the main mechanism in Moore and Healy's (2008) model of confidence is regression toward a prior: Imperfect knowledge of one's own performance and even more imperfect knowledge of others' performances makes beliefs regress toward the prior with more regression for others. In what follows we test model predictions of the SSM and the PSM on data for indirect and direct types of estimates.

Testing Model Predictions for Indirect Social Comparisons

Studies of social comparison typically use one of two methodologies: indirect or direct estimates of one's own position relative to that of others (Chambers & Windschitl, 2004). In the indirect method, people are first asked to self-report about some characteristic, such as driving ability or friendliness, and then to report about other people. Their perceived position is then indirectly inferred from the difference between self-reports and reports about others. In the direct method, people are asked how they think they compare with others on a given characteristic, and their answer is taken as their perceived social position. The indirect method of investigating people's assessments of their social position is often used in studies of social comparison to demonstrate consistent self-enhancement and self-depreciation effects, though smaller than those obtained by more direct methods (Chambers & Windschitl, 2004; Klar & Giladi, 1997; Moore, 2007).

The SSM can produce predictions for both indirect and direct social comparisons. We start with the former. We present data from one study, but we have replicated these results in two further studies conducted in the United States and Germany (see supplementary online material 5).

Procedure. We reanalyze the data obtained from a large probabilistic national sample of the Dutch population (for more details, see Study 1 in Appendix A). Participants answered questions about their own 10 characteristics, each with seven categories (e.g., seven levels of personal income). We used these self-reports to derive *true population distributions*. The participants also estimated the distributions of these characteristics in the general population of the Netherlands (*estimated population distributions*; e.g., "What percentages of adults living in the Netherlands fall into the following categories?"). Finally, 3 months later, the participants were asked to estimate the distributions of the same characteristics in their social circle (*social circle distributions*; e.g., "What percentages of your social contacts fall into the following categories?").

Empirical indirect estimates. Figure 10 presents empirical results for three characteristics with different shapes of frequency distributions: household wealth (J-left distribution), frequency of work stress (J-right), and number of friends (symmetrical distribution). Depending on the distribution shape, data for all other characteristics show similar patterns (see supplementary online material 3). Figure 10A shows true population distributions (full line), as well as average of social circle distributions (dotted line) and population estimates (dashed line). Figure 10B–D shows social circle distributions and population estimates separately for people who are "better off" (positioned at one of the three lowest levels of a particular characteristic; dashed lines) and for those who are "worse off" (positioned at one of the three lowest levels; dotted lines).

Qualitatively, the empirical results in Figure 10 and supplementary online material 3 are in line with both predictions of the SSM described before (Model Predictions section). For J-left-shaped distributions, it appears as if people were self-depreciating their own position in the population (first prediction). The easiest way to see this is in the first row of Figure 10D, where cumulative population estimates for both better-off and worse-off participants lie below the empirical population distribution (full line). Consequently, people appear to see their own positions as worse than they really are. As an illustration, Figure 10D shows guidelines depicting estimated (dashed for better-off and dotted for worse-off people) and true (full guidelines) percentiles for a hypothetical worse-off person (left of center on the x-axis) and a hypothetical better-off person (right of center on the x-axis). For J-left-shaped distributions, the guidelines for true percentiles point to a larger

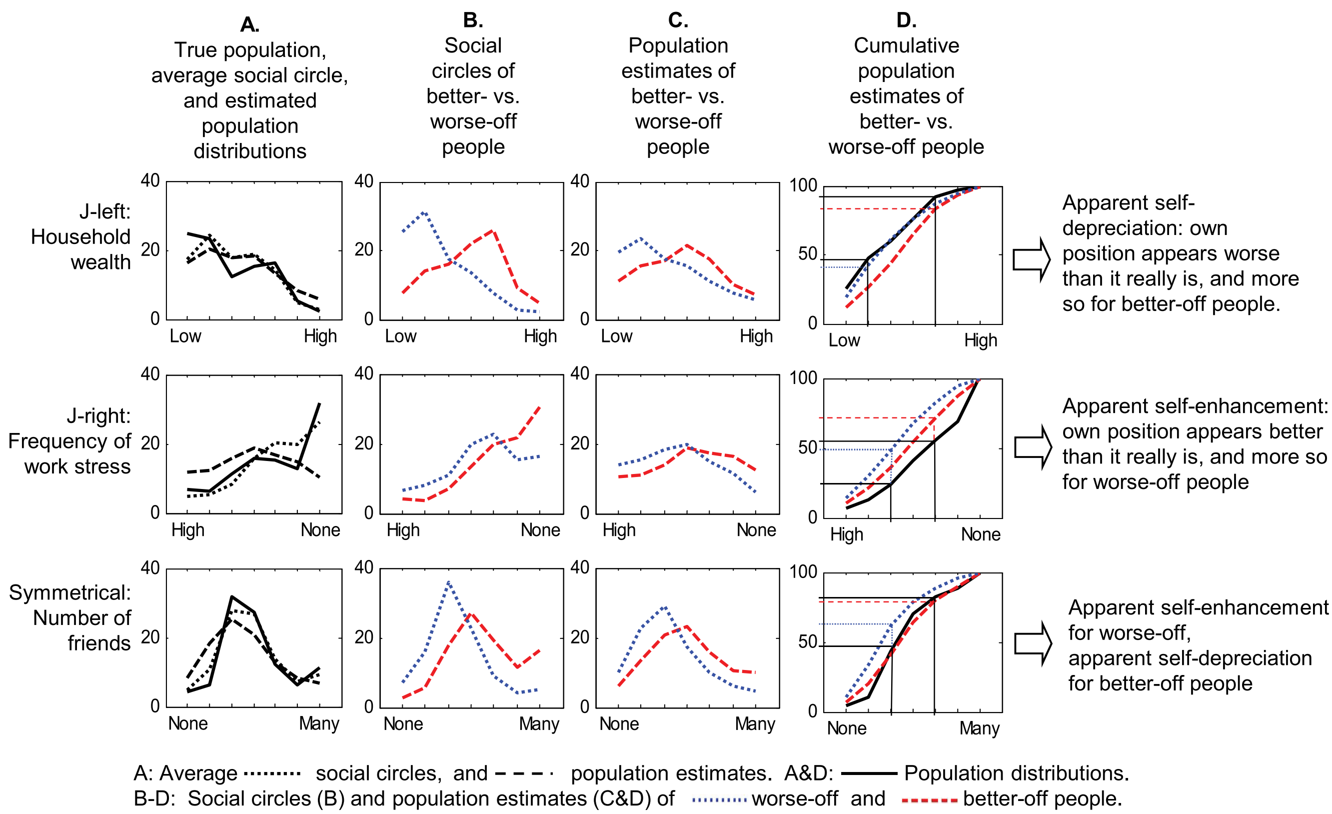

Figure 10. Estimates of population and social circle distributions for different shapes of true population distributions (A). Social circle estimates given by people who are better- versus worse-off on a given characteristic (B) resemble their population estimates (C). Cumulative population estimates (D) enable comparing their estimated population percentile with their true percentile, as indicated by the example guidelines for a hypothetical worse-off (left of center on the x-axis) and better-off (right of center) person (see text for more details). Depending on the distribution shape, the resulting patterns resemble self-depreciation, self-enhancement, or both effects. Better-off (worse-off) people are those who are positioned at one of the top (bottom) three categories of the population distribution. Figure adapted from Galesic et al. (2012). Data are from Study 1. See supplementary online material 3 for results for all characteristics included in that study. See the online article for the color version of this figure.

value on the *y*-axis than do guidelines for estimated percentiles, for both worse-off and better-off persons. In contrast, for J-right-shaped distributions, cumulative population estimates shown in the second row of Figure 10D are both above the empirical population distribution. Hence, people now appear to see their own positions as better than they really are. To illustrate, the guidelines indicating true percentiles now point to a smaller value on the *y*-axis than do the guidelines for estimated percentiles of both worse-off and better-off persons. Finally, for symmetrical distributions like the one in the third row, cumulative population estimates are above the empirical population distribution for worse-off people, suggesting self-enhancement, but below for the better-off ones who appear to exhibit self-depreciation. As an illustration, the guidelines indicating true percentiles now point to a larger value on the *y*-axis than do the guidelines for estimated percentile of the worse-off person, but to a smaller value for the better-off person.

Furthermore, in line with the second prediction described before, better-off and worse-off people give systematically different population estimates that resemble their social circles. For example, consider rows 1 and 2 in Figure 10D: Compared with better-off people, those who are worse off appear to make smaller errors in their population estimates when the underlying population distribution is J-left (resembling smaller self-depreciation effect), but larger when it is J-right shaped (resembling larger self-enhancement effect).

Implementation of the SSM and the PSM. We next implemented the SSM as described in Equations 1 and 2. The PSM was implemented in the same way, but unlike the SSM, it assumes that instances available in memory are representative of the general population and not just of one's immediate social environment. Specifically, the PSM assumes that the relative frequency of instances with different attributes corresponds to the empirical population distribution for all participants. In contrast, for the SSM it is assumed that this frequency corresponds to the distribution of instances in one's social circle. Thus, the assumption about the memory content is the crucial difference between the models.[5]

To estimate the parameter values of α and ρ, we used a grid search procedure to find values that minimize the mean square deviation between the cumulative empirical population estimates and those predicted by the two models, for each individual. With only seven data points, six degrees of freedom, and two free parameters we decided to estimate the same set of parameters across all 10 characteristics for each individual. Still, the results at the individual level are necessarily noisy and one needs to be careful drawing strong conclusions from them. We evaluated the predictions from the models at the aggregate level by comparing their average predicted cumulative distribution functions against the empirical ones. We followed a similar practice to the one used in evaluating distributional models with the predictions based on average parameter values across participants. This is commonly done, for example, when evaluating model predictions for response time distributions (e.g., when evaluating diffusion models; Gomez, Ratcliff, & Childers, 2015). Our approach differs in that we need to retain the individual social circle input in the SSM and not average the social circles over participants. Thus, we used average individual parameter estimates with individual social circles to produce aggregate level predictions. For completeness, we also evaluated how well the models capture both the average deviation and the shape of the estimated distributions at the individual level with *RMSD* and correlation as measures to decide which model predicts the data of individual participants best.

Predicting the interplay of social environments and cognitive processes. Figure 11 and supplementary online material 6 show predictions from average parameter values from the two models (SSM: $\rho = .55$, $\alpha = .47$. PSM: $\rho = .58$, $\alpha = .60$). The SSM predicts the correct ordering of the cumulative distribution functions for better-off and worse-off participants for all characteristics: The worse-off line is above the better-off line. The PSM, however, has the ordering wrong in eight of 10 characteristics. In addition to these qualitative differences, both *RMSD*s and correlations indicate that the SSM better accounts for the data across characteristics than the PSM. Across the characteristics, the median *RMSD* for better-off (worse-off) participants is 3.5 (3.6) for the SSM and 5.1 (5.2) for the PSM. The median correlation between average population estimates and predicted population estimates for better-off (worse-off) participants is .82 (.74) for the SSM and .51 (.21) for the PSM.

The SSM predicts that the average pattern of responses will resemble self-depreciation when the underlying population distribution is J-left shaped and self-enhancement when it is J-right shaped. Note, however, that the biases can be different for some individuals, depending on their social circles. Specifically, when the population distribution is J-left shaped and an individual's social circle distribution is symmetrical or J-right shaped, the SSM predicts self-enhancement, as shown in Figure 11.

At the individual level, both *RMSD*s and correlations indicated that more participants were better described with the SSM although the differences were small. The percentage of participants classified as better accounted for by the SSM (PSM) according to the *RMSD* is 53% (45%) and according to the correlation, 50% (49%). The remaining participants are equally well accounted for by both models. In sum, the exact pattern of biases can be predicted from the interplay of population distributions, social circle distributions, and cognitive processes involved in sampling from memory.

Testing Model Predictions for Direct Social Comparisons

Next, we show that the SSM also predicts self-enhancement and self-depreciation effects in direct social comparisons.

Procedure. We used data from Study 3 (see Appendix A), where participants provided not only indirect but also direct estimates of their own position in the general population.

Empirical direct estimates. Participants' direct estimates are shown in detail in supplementary online material 7. Figure 12A shows results for three example questions that represent three different distribution shapes: J-left, J-right, and symmetrical. Solid line in Figure 12B shows participants' direct estimates of their own population percentiles (*y*-axis) compared with their true population percentiles, obtained from their self-reports and true population

[5] In this article we make a clear distinction between the SSM and the PSM and treat them as competing models, but they might be considered complementary. Population-level knowledge can be glimpsed from the media or through education and combined with social circle knowledge to produce population estimates. A full account of social judgments will certainly need both processes, but their relative importance would differ depending on the specifics of the characteristics in question.

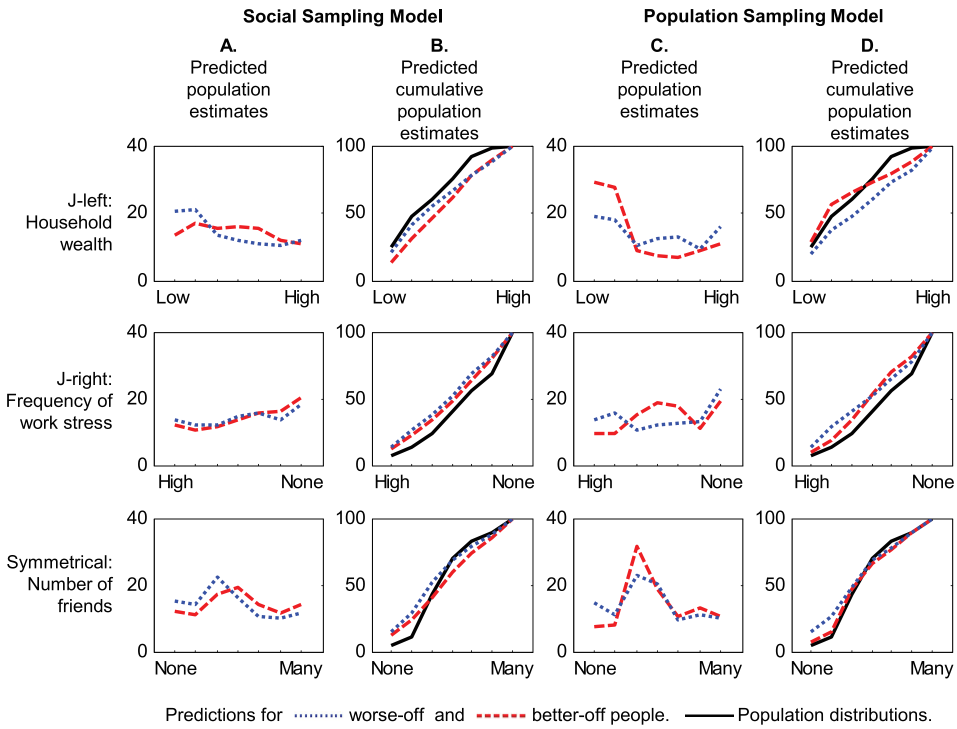

Figure 11. Predictions of the empirical population estimates shown in Figure 10, using the social sampling model (A and B) and the population sampling model (C and D). Data are from Study 1. See supplementary online material 6 for results for all characteristics included in that study. See the online article for the color version of this figure.

distributions (*x*-axis). Perfect accuracy is indicated with a dotted diagonal line, but participants' direct estimates show significant departure, as indicated by their least squares line (solid line in Figure 12B, see supplementary online material 7 for full results).

Comparison of direct and indirect estimates. Before proceeding to the description of the model predictions for the empirical patterns, we briefly compare the results obtained by asking people for their direct versus indirect estimates of their social position. As mentioned before, direct estimates were obtained by asking the participants to estimate their percentile in the general population. In addition, we inferred the indirect estimates of participants' population percentiles from their self-reports and estimated population distributions. Figure 12B shows least-square lines for a comparison of the accuracy of direct (solid line) and indirect (dashed line) estimates (see supplementary online material 7 for full results). For all characteristics, indirectly estimated percentiles are closer to participants' true population percentiles than are the directly estimated ones. In other words, people appear to have perceived their position in the general population more accurately when they were asked to estimate the whole population distribution than when they were asked to estimate only their percentile. To see this, note that the least-squares line is always steeper for indirect estimates than for direct estimates, indicating better agreement between indirectly estimated and true percentiles compared with that between directly estimated and true percentiles. Accordingly, the median correlation of indirectly estimated percentiles with the true percentiles is .79 while the correlation of directly estimated and actual percentiles is .58. Although the corresponding median *RMSD*s are large, because the actual percentiles for each category assume only a limited number of values, they are smaller for indirectly estimated percentiles ($RMSD$ = 23.4) than for direct estimates ($RMSD$ = 25.0). For comparison, the correlation between directly and indirectly estimated individual percentiles is .67, $RMSD$ = 23.3.

In sum, these results suggest that with indirect estimates of their own position in the population, people can achieve a higher level of accuracy than with direct estimates. One possible reason for our results is that in the process of estimating the whole distribution, participants searched their memories more systematically and thus reduced unsystematic noise in their estimates. These results suggest, as also pointed out by Krueger, Freestone, and MacInnis (2013), that future studies of social comparison might be more informative of people's social judgment capabilities if they use an indirect rather than direct method for studying them.

Predicted direct estimates. Next, we used the SSM and the PSM to predict participants' directly estimated percentiles. The parameters were estimated using the same procedure as before. For the United States (Germany) the average values of α and ρ for the SSM were .78 (.79) and .64 (.72), and for the PSM they were .73 (.74) and .31 (.25). Predictions of the models are shown in Figure 12C and D and in supplementary online material 7. For both countries, the SSM predicts the patterns of results better than the PSM. In the United States, the median *RMSD*s (correlations) of average predicted and average estimated percentile estimates are 30.0 (.75) for the SSM and 44.3 (.46) for the PSM. In Germany,

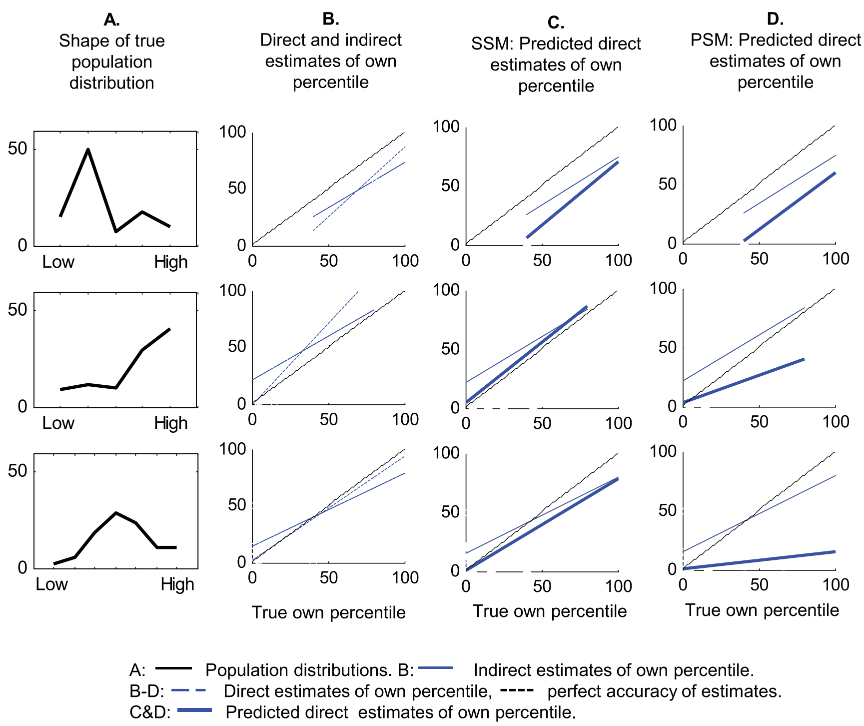

Figure 12. Estimates of participants' own percentile for characteristics with different shapes of the true population distribution (A), obtained by direct and indirect methods (B). Predictions of the social sampling model (SSM; thick lines in C) and the population sampling model (PSM; D) can be compared with empirically obtained direct estimates (thin lines in C and D). Data are from the U.S. participants in Study 3. See supplementary online material 7 for all results. See the online article for the color version of this figure.

the equivalent values are 27.3 (.58) for the SSM and 39.4 (.05) for the PSM.

At the individual level, *RMSD*s indicate that more participants are better described by the SSM (with only two data points, it was not possible to calculate correlations on the individual level). For the United States, the percentage of participants classified as better described by the SSM (PSM) according to the *RMSD* is 45% (23%). For Germany, the percentage of participants classified as better described by the SSM (PSM) according to the *RMSD* is 52% (21%). The remaining participants were equally well described by both models.

The Role of Desirability and Distribution Shape in Self-Enhancement and Self-Depreciation

We end by comparing the relative effects of desirability and distribution shape on social judgments. It has been suggested (e.g., Alicke, 1985) that self-enhancement is more likely to occur for desirable than for undesirable characteristics, as belief that one possess more desirable traits than others might bolster one's self concept (see also Chambers & Windschitl, 2004). However, it is also possible that more desirable characteristics are simply more prevalent in the general population (Fiedler, 1996; Moore & Healy, 2008; Harris & Hahn, 2011) and that self-enhancement occurs as a consequence of sampling from such J-right shaped distributions (as proposed in the SSM).

To test the relative influence of desirability and distribution shape on the occurrence of self-enhancement versus self-depreciation effects, we conducted a separate study (Study 5 in Appendix A) in which we asked $n = 100$ participants to rate the desirability of all characteristics used in Studies 1 and 3 (see methodological details about Study 5 in Appendix A). For each characteristic, we asked the participants to rate both is positive and its negative end (e.g., high and low personal income) on a 7-point scale from *very undesirable* to *very desirable*. Ratings of all characteristics, compared with ratings of items used in two of the seminal studies on self-enhancement (Alicke, 1985; and Kruger & Dunning, 1999) are provided in supplementary online material 8, Figure S8. As can be seen in Figure S8, characteristics used in our studies cover the entire range of desirability of characteristics used in previous research, suggesting that they are suitable for investigating the role of desirability in producing self-enhancement effects.

We have next examined the relationship between the extent of self-enhancement, desirability, and distribution shape for different characteristics. The extent of self-enhancement was calculated as the average error of own estimated percentile, that is the difference between one's percentile obtained from one's estimated population distribution and actual population distribution. This error is positive if the overall effect is self-enhancement and negative if it is self-depreciation. Desirability of a characteristic was determined from desirabilities of its negative and positive end. Specifically, we calculated it as the ratio of average desirability of the positive end of the characteristic (e.g., high personal income) and the sum of average desirabilities of positive and negative (e.g., low personal income) ends of the characteristic, resulting in a relative desirability $D_{rel} = D_{pos.end}/(D_{neg.end} + D_{pos.end})$. Distribution shape for a characteristic was calculated as the difference between proportion of the population in categories to the right and to the left of the central response option, $S = p_{right}$ - p_{left}.

As shown in Figure 13, the extent of self-enhancement was only weakly related to the desirability of characteristics. In Study 1 in the Netherlands the correlation was $r = .32$ ($p = .37$), while in Study 3 it was $r = .17$ ($p = .66$) in the U.S., and $r = .31$ ($p = .43$) in Germany. In contrast, self-enhancement was strongly related to the shape of population distribution ($r = .98$, .98, and .91 in the three countries, respectively; all $p < .001$). After partialing out the effect of shape, the effect of desirability remained unreliable and highly variable across studies: r(error, desirability).shape $= -.51$ ($p = .16$), .49 ($p = .22$) and .26 ($p = .54$) in the three countries, respectively. In contrast, after partialing out the effect of desirability, the effect of shape remained strong: r(error, shape).desirability = .98, .98, and .91 (all $p < .002$). These results are in line with the SSM assumptions and replicate previous findings (Kruger, 1999; Moore & Small, 2007). They suggest that distribution shape, not desirability of characteristics, is the driving factor of self-enhancement and self-depreciation effects.

General Discussion

We proposed and tested a quantitative process model of social judgment, the social sampling model (SSM). We provided evidence that people's reports about their social circles are valid and reliable, and that they are used to produce population estimates, as assumed by the SSM. In accordance with the SSM's predictions we demonstrated four principal results. First, false consensus was observed when social circles were characterized by strong homophily and false uniqueness when social circles had weak homophily. Second, patterns of false consensus and false uniqueness can be produced simply by using different question formats. Third, population estimates appeared as if they were affected by self-enhancement when the underlying distribution in the general population was J-right shaped and by self-depreciation when the underlying distribution was J-left shaped. Fourth, people who were worse off on a particular characteristic showed systematically different errors in their population estimates compared with people who were better off on that characteristic. These effects were observed for both indirect and direct estimates of participants' own position in the distributions, with indirect estimates of their own

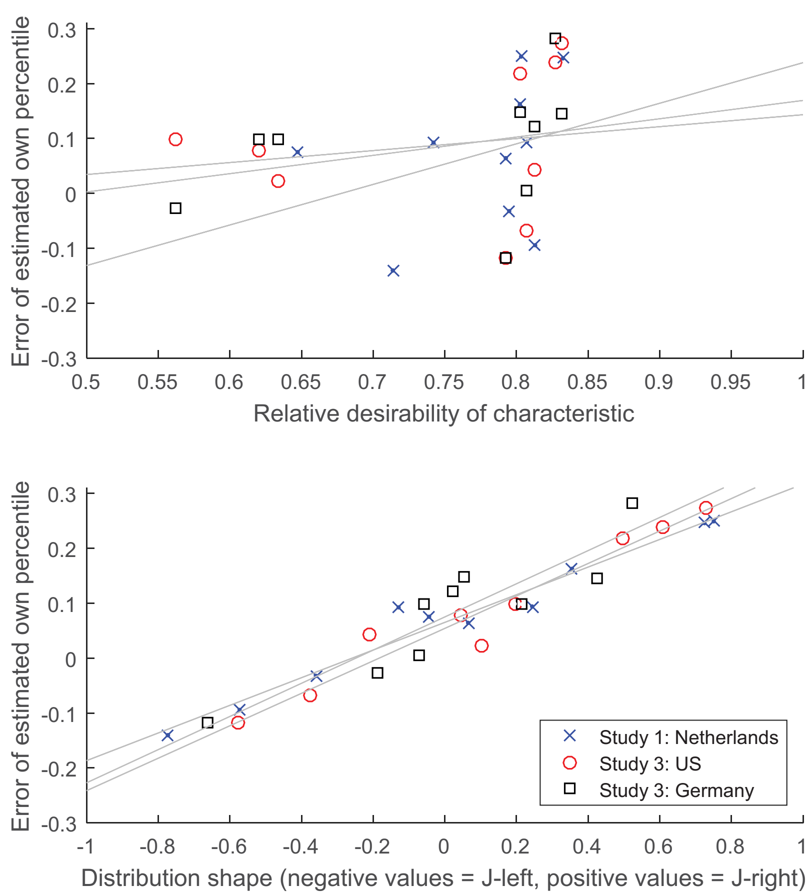

Figure 13. Relationship between extent of self-enhancement (i.e., error of estimated own percentile, with positive values resembling self-enhancement and negative values resembling self-depreciation) and relative desirability (A) and distribution shape (B) of characteristics used in Studies 1 and 3. See the online article for the color version of this figure.

position in the population achieving higher accuracy than direct ones.

The SSM makes the novel contribution of specifying a general process model of social judgment that provides a description of the underlying cognitive process of judgments and explains diverse social judgment phenomena. While the SSM might not include all of the factors that cause phenomena such as false consensus and self-enhancement, it provides a reasonable baseline that can be used to evaluate whether these effects require further explanation in terms of additional cognitive or motivational processes. In addition, the precise formalization of the assumed underlying processes enables quantitative predictions that can be empirically confirmed or disconfirmed, stimulating further theoretical debate and model development.

In the following we discuss implications of our theoretical predictions and empirical findings for public policy programs and for understanding hidden social dynamics. Furthermore, we discuss how our theory can explain other results in the social judgment literature and how the SSM can be further extended.

Implications for Public Policy Programs

Public policy efforts are often aimed at decreasing divisions that exist in the general public along socioeconomic, racial, and ideological lines. The SSM predicts that judgments of beliefs and behaviors present in broader social environments are likely to be distorted, the more so the more homophilous one's social circle. If people have never encountered a representative of a particular group, this group will not be included in their population estimates without utilizing some further sources of information. This can affect their beliefs about benefits of different social policies. For instance, Dawtry, Sutton, and Sibley (2015) found that people's estimates of wealth distributions depended on the wealth of their own social circles, and that wealthier people were more likely to oppose redistribution policies. Public programs therefore might aim at improving people's knowledge about the general population, for example by providing appropriately formatted information about the population frequencies (Trevena et al., 2013), especially to people living in relatively isolated social circles. In addition, in line with the contact hypothesis (Dovidio, Eller, & Hewstone, 2011), public policy programs could aim to actively introduce diversity in people's immediate social environments, and consequently their social memories, by fostering education about and exposure to alternative opinions and lifestyles. Such programs are increasingly important given recent indications about increased homophily in some segments of the society, possibly due to the ease of creating communities of like-minded others on social media (Galesic et al., 2018; Quattrociocchi, Scala, & Sunstein, 2016; Thompson, 2016). According to the SSM, higher homophily will often lead to decreased accuracy of judgments about characteristics (for instance, different beliefs and behaviors) of broader populations because people's social samples will be less representative for these populations (see Are Social Circles Used to Produce Population Estimates section). Through processes of social influence, this in turn can affect people's own beliefs and behaviors, making them less likely to change (Huckfeldt & Sprague, 1995; Sinclair, 2012).

Implications for Understanding Hidden Social Dynamics

The SSM also suggests that it might be possible to investigate hidden social dynamics in a population by using people's estimates of their social circles to construct a more accurate picture of the general population. So far, surveys of beliefs and behaviors in the general population have almost exclusively relied on self-reports of participants. However, these might suffer from social desirability distortions, and rare beliefs and behaviors may be difficult to capture in smaller surveys whose sample sizes do not exceed about a thousand participants. Collecting individuals' knowledge about their immediate social environments might usefully complement self-reports. Some previous studies asked participants about their population estimates about, for example, election results and noted that predictions based on these population estimates can be as accurate as, if not more accurate than, standard survey estimates based on self-reports (Graefe, 2014). Because the SSM predicts systematic biases in people's population estimates, we expect that forecasting election results based on people's estimates of voting patterns in their social circles might achieve even higher accuracy. We found confirming evidence for this prediction in studies predicting election results in the 2016 U.S. and 2017 French presidential elections (Galesic et al., 2018). More generally, utilizing people's social wisdom might illuminate hard-to-detect patterns of social dynamics such as the spread of potentially harmful ideas which people would not readily admit in surveys, or whose proponents might not participate in surveys for various reasons (e.g., that violence may be an acceptable way to achieve political goals, or that MMR vaccination should be optional).

Individual Differences and Further Process Predictions

The process nature of the SSM enables future investigations of how individual differences affect parameter estimates and judgment accuracy. For instance, frequency of contact is likely related to successful recall of social information (see, e.g., Hills & Pachur, 2012). Consequently, when the SSM is used to predict participants' population estimates on the basis of the social contacts they encounter less frequently, the resulting parameter recall probability parameter α should be lower than when the input to the SSM is their more frequent contacts. Furthermore, homophily introduces a correlation between frequency of contact with someone and the similarity of that person to oneself, making more frequent contacts less representative of a broader social environment. This should lead to a lower similarity parameter ρ when the input to the SSM are more frequent social contacts compared to infrequent social contacts. By asking about social circles in different ways—prompting inclusion of more or less frequent social contacts—one can investigate if α and ρ behave as expected. In addition, participants with more homophilous social circles should have lower values of ρ.

Extending the SSM

Other sources of information. In the present formulation of the SSM, we assumed that social judgments about broader populations are based only on the knowledge people have about their social circles. An extension of the SSM could incorporate other sources of information, such as egocentric information or additional knowledge from other sources such as the media.

In the current version of the SSM we did not explicitly model the potential influence of self-knowledge. The anchoring and adjustment view of the social judgment process (e.g., Kruger, 1999), where people anchor on their own value and insufficiently adjust it to produce a judgment, does not specify the underlying processes. One way of implementing the egocentric view in the general framework of the SSM is to assume that people do not disregard information about people like themselves but instead disregard information about people that are not like themselves. By comparing how well the original SSM and the egocentric version of SSM predict empirical data we could establish to what extent people rely more on egocentric information (in the sense that they rely on information about retrieved information about people that are like them) or disregard information about people that are like themselves.

For some characteristics, people may use additional knowledge about the general population available in the media or obtained through education. For instance, people might know the approximate shape of income distributions or the distribution of political preferences in the country, as those often appear in the media. In contrast, judgments about characteristics such as conflicts with a partner or work stress are more likely to be based only on one's own social circle knowledge. In the SSM, the effect of the media can be modeled as an additional input in the social sampling process, augmenting the information from social circles. The relative influence of media versus social circle information will depend on the amount of time people spend acquiring information about different issues from the media versus by discussing the issues with their social contacts. This parameter does not have to be estimated from the data but can be measured directly by asking people about the time they spent on each of these activities. Once social memory is modeled as a combination of both a person's social circle and media reports, the rest of the social sampling process can be modeled as before using Equation 1. Initial support for the feasibility of this approach has been found by Galesic, Kaemmer, Olsson, and Rieskamp (2014), who investigated people's judgments about likely population voting patterns in the 2013 German parliamentary elections.

Lack of information. The frequency of some characteristics is difficult to judge because they are rarely displayed in public (Jordan et al., 2011). For example, negative emotions are often publicly suppressed, particularly on social media (Kross et al., 2013). Consequently, estimates of the prevalence of these characteristics in one's social circle could be erroneous, inflating the errors in resulting population estimates. This, however, does not impair the SSM's ability to predict people's population estimates, as the model relies on experienced rather than actual characteristics of social environments. It could therefore be used to predict precisely how people in different social environments would estimate population distributions and how they would consequently evaluate their own characteristics. For example, it has been observed that the apparent positive affect of others on social media might undermine individuals' well-being because they might think they are doing worse than they really are (Verduyn et al., 2015). The SSM could provide more nuanced predictions of the extent of such effects, identify segments of the population prone to such harmful misperceptions, and help in design of alleviating interventions (e.g., by providing information about true population distributions).

Sampling and memory processes. In the SSM, we kept the sampling and memory assumptions simple, opening several possibilities for the model to be extended. Regarding sampling processes we assumed and found empirical support for a self-similarity sampling cue, but there are other possibilities that can be explored such as cues that utilize surface similarities between own social contacts and the reference class (e.g., gender or location). It might also be possible to minimize the use of free parameters in determining the sample used for population judgments. In the present article, similarity parameter ρ was estimated, but in future studies it might be possible to approximate ρ by asking people how often they meet people outside their social circle, follow the media, and so forth. Moreover, in the present formulation of the SSM, we do not make any strong assumptions about the nature of the retrieval process. The process might be serial or parallel and we do not assume that instances are explicitly counted or even consciously activated. The SSM could be extended with precise models of the retrieval process. Given the exemplar flavor of the SSM, a natural extension would be to investigate the possibility of integrating parts of the process assumptions in an exemplar-based sequential sampling model of categorization (Nosofsky & Palmeri, 1997), memory (Nosofsky, Cao, Cox, & Shiffrin, 2014), or estimation (Juslin & Persson, 2002). In these models, judgments are determined by the accumulation of evidence from exemplars. In terms of the SSM, the parameter ρ would then act as a stopping rule or decision boundary that determines when enough information is sampled and a judgment is made. This would also allow the SSM to produce predictions of response times. Another possibility is to reformulate the memory process in terms of a connectionist model. There are several connectionist architectures that have been applied to results in the social cognition literature, such as constraint satisfaction (Kunda & Thagard, 1996) and recurrent networks (Van Rooy et al., 2003). Formulating the SSM as a connectionist model, however, seems at present more difficult than formulating it as an exemplar-based sequential sampling model, as there is not a clear mapping between the processes and parameters in the SSM and most of the connectionist modeling attempts in social cognition.

Conclusion

In the ecological approach to cognition (e.g., Anderson, 1990; Fiedler & Juslin, 2006; Gigerenzer et al., 1999), the mind is not an isolated entity but must be studied as a part of a complex system of minds embedded in particular social and task environments. Following this approach, we presented a model that explains the origin of social judgments and various related phenomena that were so far not parsimoniously explained. The SSM provides quantitative predictions of these phenomena by formalizing sampling mechanisms that are sensitive to the structure of social and task environments. The model allows for precise empirical tests of its assumptions and predictions, opening the door for further theoretical development and advancing our understanding of the importance of nurturing diversity in our social environments.

References

Alicke, M. D. (1985). Global self-evaluation as determined by the desirability and controllability of trait adjectives. *Journal of Personality and Social Psychology, 49,* 1621–1630. http://dx.doi.org/10.1037/0022-3514.49.6.1621

Alicke, M. D., & Govorun, O. (2005). The better-than-average effect. In M. D. Alicke, D. A. Dunning, & J. I. Krueger (Eds.), *The self in social judgment: Studies in self and identity* (pp. 85–106). New York, NY: Psychology Press.

Alicke, M. D., Klotz, M. L., Breitenbecher, D. L., Yurak, T. J., & Vredenburg, D. S. (1995). Personal contact, individuation, and the better-than-average effect. *Journal of Personality and Social Psychology, 68,* 804–825. http://dx.doi.org/10.1037/0022-3514.68.5.804

Allbus. (2010). *Allbus: Die Allgemeine Bevoelkerungsumfrage der Sozialwissenschaften*. Retrieved from https://www.gesis.org/allbus/inhalte-suche/studienprofile-1980-bis-2016/2010/

Anderson, J. R. (1990). *The adaptive character of thought*. Hillsdale, NJ: Erlbaum.

Anderson, J. R., & Lebiere, C. (1998). *The atomic components of thought*. Mahwah, NJ: Erlbaum.

Behavioral Risk Factor Surveillance System Survey. (2010). *Survey data & documentation*. Retrieved from https://www.cdc.gov/brfss/data_documentation/index.htm

Brown, G. D. A., Wood, A. M., Ogden, R. S., & Maltby, J. (2015). Do student evaluations of university reflect inaccurate beliefs or actual experience? A relative rank model. *Journal of Behavioral Decision Making, 28,* 14–26. http://dx.doi.org/10.1002/bdm.1827

Brown, J. D. (2012). Understanding the better than average effect: Motives (still) matter. *Personality and Social Psychology Bulletin, 38,* 209–219. http://dx.doi.org/10.1177/0146167211432763

Burson, K. A., Larrick, R. P., & Klayman, J. (2006). Skilled or unskilled, but still unaware of it: How perceptions of difficulty drive miscalibration in relative comparisons. *Journal of Personality and Social Psychology, 90,* 60–77. http://dx.doi.org/10.1037/0022-3514.90.1.60

Chambers, J. R., & Windschitl, P. D. (2004). Biases in social comparative judgments: The role of nonmotivated factors in above-average and comparative-optimism effects. *Psychological Bulletin, 130,* 813–838. http://dx.doi.org/10.1037/0033-2909.130.5.813

Christakis, N. A., & Fowler, J. H. (2007). The spread of obesity in a large social network over 32 years. *The New England Journal of Medicine, 357,* 370–379. http://dx.doi.org/10.1056/NEJMsa066082

Christakis, N. A., & Fowler, J. H. (2008). The collective dynamics of smoking in a large social network. *The New England Journal of Medicine, 358,* 2249–2258. http://dx.doi.org/10.1056/NEJMsa0706154

Coleman, J. (1958). Relational analysis: The study of social organizations with survey methods. *Human Organization, 17,* 28–36. http://dx.doi.org/10.17730/humo.17.4.q5604m676260q8n7

Dawes, R. M. (1989). Statistical criteria for establishing a truly false consensus effect. *Journal of Experimental Social Psychology, 25,* 1–17. http://dx.doi.org/10.1016/0022-1031(89)90036-X

Dawes, R. M., & Mulford, M. (1996). The false consensus effect and overconfidence: Flaws in judgment or flaws in how we study judgment? *Organizational Behavior and Human Decision Processes, 65,* 201–211. http://dx.doi.org/10.1006/obhd.1996.0020

Dawtry, R. J., Sutton, R. M., & Sibley, C. G. (2015). Why wealthier people think people are wealthier, and why it matters: From social sampling to attitudes to redistribution. *Psychological Science, 26,* 1389–1400. http://dx.doi.org/10.1177/0956797615586560

Dovidio, J. F., Eller, A., & Hewstone, M. (2011). Improving intergroup relations through direct, extended and other forms of indirect contact. *Group Processes & Intergroup Relations, 14,* 147–160. http://dx.doi.org/10.1177/1368430210390555

Dunning, D., & Hayes, A. F. (1996). Evidence for egocentric comparison in social judgment. *Journal of Personality and Social Psychology, 71,* 213–229. http://dx.doi.org/10.1037/0022-3514.71.2.213

Ehrlinger, J., Johnson, K., Banner, M., Dunning, D., & Kruger, J. (2008). Why the unskilled are unaware: Further explorations of (absent) self-insight among the incompetent. *Organizational Behavior and Human Decision Processes, 105,* 98–121. http://dx.doi.org/10.1016/j.obhdp.2007.05.002

Epley, N., & Dunning, D. (2006). The mixed blessings of self-knowledge in behavioral prediction: Enhanced discrimination but exacerbated bias. *Personality and Social Psychology Bulletin, 32,* 641–655. http://dx.doi.org/10.1177/0146167205284007

Epley, N., Keysar, B., Van Boven, L., & Gilovich, T. (2004). Perspective taking as egocentric anchoring and adjustment. *Journal of Personality and Social Psychology, 87,* 327–339. http://dx.doi.org/10.1037/0022-3514.87.3.327

Erev, I., Wallsten, T. S., & Budescu, D. V. (1994). Simultaneous over-and underconfidence: The role of error in judgment processes. *Psychological Review, 101,* 519–527. http://dx.doi.org/10.1037/0033-295X.101.3.519

Festinger, L. (1954). A theory of social comparison processes. *Human Relations, 7,* 117–140. http://dx.doi.org/10.1177/001872675400700202

Fiedler, K. (1996). Explaining and simulating judgment biases as an aggregation phenomenon in probabilistic, multiple-cue environments. *Psychological Review, 103,* 193–214. http://dx.doi.org/10.1037/0033-295X.103.1.193

Fiedler, K. (2000). Beware of samples! A cognitive-ecological sampling approach to judgment biases. *Psychological Review, 107,* 659–676. http://dx.doi.org/10.1037/0033-295X.107.4.659

Fiedler, K., & Juslin, P. (Eds.). (2006). *Information sampling and adaptive cognition*. New York, NY: Cambridge University Press.

Fiedler, K., Unkelbach, C., & Freytag, P. (2009). On splitting and merging categories: A regression account of subadditivity. *Memory & Cognition, 37,* 383–393. http://dx.doi.org/10.3758/MC.37.4.383

Fields, J. M., & Schuman, H. (1976). Public beliefs about the beliefs of the public. *Public Opinion Quarterly, 40,* 427–448. http://dx.doi.org/10.1086/268330

Frable, D. E. S. (1993). Being and feeling unique: Statistical deviance and psychological marginality. *Journal of Personality, 61,* 85–110. http://dx.doi.org/10.1111/j.1467-6494.1993.tb00280.x

Fu, F., Nowak, M. A., Christakis, N. A., & Fowler, J. H. (2012). The evolution of homophily. *Scientific Reports, 2,* 845. http://dx.doi.org/10.1038/srep00845

Galesic, M., Bruine de Bruin, W., Dumas, M., Kapteyn, A., Darling, J. E., & Meijer, E. (2018). Asking about social circles improves election predictions. *Nature Human Behaviour, 2,* 187–193. http://dx.doi.org/10.1038/s41562-018-0302-y

Galesic, M., Kaemmer, J., Olsson, H., & Rieskamp, J. (2014, July). *A process model of social sampling*. Paper presented at the European Association of Social Psychology Conference, Amsterdam, the Netherlands.

Galesic, M., Olsson, H., & Rieskamp, J. (2012). Social sampling explains apparent biases in judgments of social environments. *Psychological Science, 23,* 1515–1523. http://dx.doi.org/10.1177/0956797612445313

Galesic, M., Olsson, H., & Rieskamp, J. (2013). False consensus about consensus. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), In *Proceedings of the 35th annual conference of the cognitive science society* (pp. 472–476). Austin, TX: Cognitive Science Society.

Gallup. (2011). *What the whole world is thinking: Gallup World Poll*. Retrieved from http://www.gallup.com/services/170945/worldpoll.aspx

General Social Survey. (2010). *Get the data*. Retrieved from http://gss.norc.org/get-the-data

Gigerenzer, G., Todd, P. M., & the ABC Research Group. (1999). *Simple heuristics that make us smart*. New York, NY: Oxford University Press.

Gomez, P., Ratcliff, R., & Childers, R. (2015). Pointing, looking at, and pressing keys: A diffusion model account of response modality. *Journal* *of Experimental Psychology: Human Perception and Performance, 41,* 1515–1523. http://dx.doi.org/10.1037/a0039653

Graefe, A. (2014). Accuracy of vote expectation surveys in forecasting elections. *Public Opinion Quarterly, 78,* 204–232. http://dx.doi.org/10.1093/poq/nfu008

Harris, A. J. L., & Hahn, U. (2011). Unrealistic optimism about future life events: A cautionary note. *Psychological Review, 118,* 135–154. http://dx.doi.org/10.1037/a0020997

Heck, P. R., & Krueger, J. I. (2015). Self-enhancement diminished. *Journal of Experimental Psychology: General, 144,* 1003–1020. http://dx.doi.org/10.1037/xge0000105

Hertwig, R., Hoffrage, U., & the ABC Research Group. (2013). *Simple heuristics in a social world*. New York, NY: Oxford University Press.

Hilbert, M. (2012). Toward a synthesis of cognitive biases: How noisy information processing can bias human decision making. *Psychological Bulletin, 138,* 211–237. http://dx.doi.org/10.1037/a0025940

Hills, T. T., & Pachur, T. (2012). Dynamic search and working memory in social recall. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 38,* 218–228. http://dx.doi.org/10.1037/a0025161

Huckfeldt, R. R., & Sprague, J. (1995). *Citizens, politics and social communication: Information and influence in an election campaign*. New York, NY: Cambridge University Press. http://dx.doi.org/10.1017/CBO9780511664113

Jordan, A. H., Monin, B., Dweck, C. S., Lovett, B. J., John, O. P., & Gross, J. J. (2011). Misery has more company than people think: Underestimating the prevalence of others' negative emotions. *Personality and Social Psychology Bulletin, 37,* 120–135. http://dx.doi.org/10.1177/0146
167210390822

Judd, C. M., Ryan, C. S., & Park, B. (1991). Accuracy in the judgment of in-group and out-group variability. *Journal of Personality and Social Psychology, 61,* 366–379. http://dx.doi.org/10.1037/0022-3514.61.3.366

Juslin, P., & Persson, M. (2002). PROBabilities from EXemplars (PROBEX): A "lazy" algorithm for probabilistic inference from generic knowledge. *Cognitive Science, 26,* 563–607. http://dx.doi.org/10.1207/s15516709cog2605_2

Juslin, P., Wennerholm, P., & Olsson, H. (1999). Format dependence in subjective probability calibration. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 25,* 1038–1052. http://dx.doi.org/10.1037/0278-7393.25.4.1038

Juslin, P., Winman, A., & Hansson, P. (2007). The naïve intuitive statistician: A naïve sampling model of intuitive confidence intervals. *Psychological Review, 114,* 678–703. http://dx.doi.org/10.1037/0033-295X.114.3.678

Juslin, P., Winman, A., & Olsson, H. (2000). Naive empiricism and dogmatism in confidence research: A critical examination of the hard-easy effect. *Psychological Review, 107,* 384–396. http://dx.doi.org/10.1037/0033-295X.107.2.384

Kaczmirek, L. (2014). *A framework for the collection of universal client side paradata (UCSP)*. Retrieved from http://kaczmirek.de/ucsp/ucsp.html

Kennedy, C., Zsolt, N., Pierangelo, I., Philip, E., & Eichenberg, R. (2011). *Transatlantic Trends Survey*. Retrieved from http://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/34422

Klar, Y., & Giladi, E. E. (1997). No one in my group can be below the group's average: A robust positivity bias in favor of anonymous peers. *Journal of Personality and Social Psychology, 73,* 885–901. http://dx.doi.org/10.1037/0022-3514.73.5.885

Kreuter, F. (Ed.). (2013), *Improving surveys with paradata*. New York, NY: Wiley.

Kross, E., Verduyn, P., Demiralp, E., Park, J., Lee, D. S., Lin, N., . . . Ybarra, O. (2013). Facebook use predicts declines in subjective well-being in young adults. *PLoS ONE, 8,* e69841. http://dx.doi.org/10.1371/journal.pone.0069841

Krueger, J. (1998). On the perception of social consensus. *Advances in Experimental Social Psychology, 30,* 163–240. http://dx.doi.org/10.1016/S0065-2601(08)60384-6

Krueger, J. (2000). The projective perception of the social world. In J. Suls & L. Wheeler (Eds.), *Handbook of social comparison: Theory and research* (pp. 323–351). Boston, MA: Springer. http://dx.doi.org/10.1007/978-1-4615-4237-7_16

Krueger, J. I. (2007). From social projection to social behaviour. *European Review of Social Psychology, 18,* 1–35. http://dx.doi.org/10.1080/10463280701284645

Krueger, J., & Clement, R. W. (1994). The truly false consensus effect: An ineradicable and egocentric bias in social perception. *Journal of Personality and Social Psychology, 67,* 596–610. http://dx.doi.org/10.1037/0022-3514.67.4.596

Krueger, J., & Clement, R. W. (1997). Estimates of social consensus by majorities and minorities: The case for social projection. *Personality and Social Psychology Review, 1,* 299–313. http://dx.doi.org/10.1207/s15327957pspr0104_2

Krueger, J. I., Freestone, D., & MacInnis, M. L. (2013). Comparisons in research and reasoning: Toward an integrative theory of social induction. *New Ideas in Psychology, 31,* 73–86. http://dx.doi.org/10.1016/j.newideapsych.2012.11.002

Krueger, J. I., & Funder, D. C. (2004). Towards a balanced social psychology: Causes, consequences, and cures for the problem-seeking approach to social behavior and cognition. *Behavioral and Brain Sciences, 27,* 313–327. http://dx.doi.org/10.1017/S0140525X04000081

Krueger, J., & Mueller, R. A. (2002). Unskilled, unaware, or both? The better-than-average heuristic and statistical regression predict errors in estimates of own performance. *Journal of Personality and Social Psychology, 82,* 180–188. http://dx.doi.org/10.1037/0022-3514.82.2.180

Kruger, J. (1999). Lake Wobegon be gone! The "below-average effect" and the egocentric nature of comparative ability judgments. *Journal of Personality and Social Psychology, 77,* 221–232. http://dx.doi.org/10.1037/0022-3514.77.2.221

Kruger, J., & Dunning, D. (1999). Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments. *Journal of Personality and Social Psychology, 77,* 1121–1134. http://dx.doi.org/10.1037/0022-3514.77.6.1121

Kruschke, J. K. (1992). ALCOVE: An exemplar-based connectionist model of category learning. *Psychological Review, 99,* 22–44. http://dx.doi.org/10.1037/0033-295X.99.1.22

Kunda, Z., & Thagard, P. (1996). Forming impressions from stereotypes, traits, and behaviors: A parallel constraint satisfaction theory. *Psychological Review, 103,* 284–308. http://dx.doi.org/10.1037/0033-295X.103.2.284

Linville, P. W., Fischer, G. W., & Salovey, P. (1989). Perceived distributions of the characteristics of in-group and out-group members: Empirical evidence and a computer simulation. *Journal of Personality and Social Psychology, 57,* 165–188. http://dx.doi.org/10.1037/0022-3514.57.2.165

Loughnan, S., Kuppens, P., Allik, J., Balazs, K., de Lemus, S., Dumont, K., . . . Haslam, N. (2011). Economic inequality is linked to biased self-perception. *Psychological Science, 22,* 1254–1258. http://dx.doi.org/10.1177/0956797611417003

Marks, G., & Miller, N. (1987). Ten years of research on the false-consensus effect: An empirical and theoretical review. *Psychological Bulletin, 102,* 72–90. http://dx.doi.org/10.1037/0033-2909.102.1.72

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology, 27,* 415–444. http://dx.doi.org/10.1146/annurev.soc.27.1.415

Moore, D. A. (2007). When good = better than average. *Judgment and Decision Making, 2,* 277–291.

Moore, D. A., & Healy, P. J. (2008). The trouble with overconfidence. *Psychological Review, 115,* 502–517. http://dx.doi.org/10.1037/0033-295X.115.2.502

Moore, D. A., & Kim, T. G. (2003). Myopic social prediction and the solo comparison effect. *Journal of Personality and Social Psychology, 85,* 1121–1135. http://dx.doi.org/10.1037/0022-3514.85.6.1121

Moore, D. A., & Small, D. A. (2007). Error and bias in comparative judgment: On being both better and worse than we think we are. *Journal of Personality and Social Psychology, 92,* 972–989. http://dx.doi.org/10.1037/0022-3514.92.6.972

Mullen, B., Atkins, J. L., Champion, D. S., Edwards, C., Hardy, D., Story, J. E., & Vanderklok, M. (1985). The false consensus effect: A meta-analysis of 115 hypothesis tests. *Journal of Experimental Social Psychology, 21,* 262–283. http://dx.doi.org/10.1016/0022-1031(85)90020-4

Mullen, B., Dovidio, J. F., Johnson, C., & Copper, C. (1992). In-group-out-group differences in social projection. *Journal of Experimental Social Psychology, 28,* 422–440. http://dx.doi.org/10.1016/0022-1031(92)90040-Q

Nisbett, R. E., & Kunda, Z. (1985). Perception of social distributions. *Journal of Personality and Social Psychology, 48,* 297–311. http://dx.doi.org/10.1037/0022-3514.48.2.297

Nosofsky, R. M. (1986). Attention, similarity, and the identification-categorization relationship. *Journal of Experimental Psychology: General, 115,* 39–57.

Nosofsky, R. M., Cao, R., Cox, G. E., & Shiffrin, R. M. (2014). Familiarity and categorization processes in memory search. *Cognitive Psychology, 75,* 97–129. http://dx.doi.org/10.1016/j.cogpsych.2014.08.003

Nosofsky, R. M., & Palmeri, T. J. (1997). An exemplar-based random walk model of speeded classification. *Psychological Review, 104,* 266–300. http://dx.doi.org/10.1037/0033-295X.104.2.266

Pachur, T., Hertwig, R., & Rieskamp, J. (2013). Intuitive judgments of social statistics: How exhaustive does sampling need to be? *Journal of Experimental Social Psychology, 49,* 1059–1077. http://dx.doi.org/10.1016/j.jesp.2013.07.004

Parducci, A. (1965). Category judgment: A range-frequency model. *Psychological Review, 72,* 407–418. http://dx.doi.org/10.1037/h0022602

Parducci, A. (1995). *Happiness, pleasure, and judgment: The context theory and its applications*. Mahwah, NJ: Erlbaum.

Pew Research Center. (2011). *The American-Western European Values Gap*. Retrieved from http://www.pewglobal.org/2011/11/17/the-american-western-european-values-gap/

Quattrociocchi, W., Scala, A., & Sunstein, C. R. (2016, June). *Echo chambers on Facebook*. Retrieved from the Social Science Research Network, https://ssrn.com/abstract=2795110

Robbins, J. M., & Krueger, J. I. (2005). Social projection to ingroups and outgroups: A review and meta-analysis. *Personality and Social Psychology Review, 9,* 32–47. http://dx.doi.org/10.1207/s15327957pspr0901_3

Roese, N. J., & Olson, J. M. (2007). Better, stronger, faster: Self-serving judgment, affect regulation, and the optimal vigilance hypothesis. *Perspectives on Psychological Science, 2,* 124–141. http://dx.doi.org/10.1111/j.1745-6916.2007.00033.x

Rosenquist, J. N., Murabito, J., Fowler, J. H., & Christakis, N. A. (2010). The spread of alcohol consumption behavior in a large social network. *Annals of Internal Medicine, 152,* 426–433. http://dx.doi.org/10.7326/0003-4819-152-7-201004060-00007

Ross, L., Greene, D., & House, P. (1977). The "false consensus effect:" An egocentric bias in social perception and attribution processes. *Journal of Experimental Social Psychology, 13,* 279–301. http://dx.doi.org/10.1016/0022-1031(77)90049-X

Roy, M. M., Liersch, M. J., & Broomell, S. (2013). People believe that they are prototypically good or bad. *Organizational Behavior and Human Decision Processes, 122,* 200–213. http://dx.doi.org/10.1016/j.obhdp.2013.07.004

Schiller, J. S., Lucas, J. W., Ward, B. W., & Peregoy, J. A. (2010). *Summary health statistics for U.S. adults: National Health Interview Survey*. Hyattsville, Maryland: National Center for Health Statistics. Retrieved from https://www.cdc.gov/nchs/data/series/sr_10/sr10_252.pdf

Sedikides, C., Gaertner, L., & Toguchi, Y. (2003). Pancultural self-enhancement. *Journal of Personality and Social Psychology, 84,* 60–79. http://dx.doi.org/10.1037/0022-3514.84.1.60

Signorile, V., & O'Shea, R. M. (1965). A test of significance for the homophily index. *American Journal of Sociology, 70,* 467–470. http://dx.doi.org/10.1086/223880

Simon, H. A. (1996). *The sciences of the artificial* (3rd ed.). Cambridge, MA: MIT Press.

Sinclair, B. (2012). *The social citizen: Peer networks and political behavior*. Chicago, IL: University of Chicago Press. http://dx.doi.org/10.7208/chicago/9780226922836.001.0001

Smith, E. R., & Collins, E. C. (2009). Contextualizing person perception: Distributed social cognition. *Psychological Review, 116,* 343–364. http://dx.doi.org/10.1037/a0015072

Smith, E. R., & Conrey, F. R. (2007). Agent-based modeling: A new approach for theory building in social psychology. *Personality and Social Psychology Review, 11,* 87–104. http://dx.doi.org/10.1177/1088868306294789

Smith, E. R., & Zarate, M. A. (1992). Exemplar-based model of social judgment. *Psychological Review, 99,* 3–21. http://dx.doi.org/10.1037/0033-295X.99.1.3

Smith, R. H., Diener, E., & Wedell, D. H. (1989). Intrapersonal and social comparison determinants of happiness: A range-frequency analysis. *Journal of Personality and Social Psychology, 56,* 317–325. http://dx.doi.org/10.1037/0022-3514.56.3.317

Stewart, N., Chater, N., & Brown, G. D. A. (2006). Decision by sampling. *Cognitive Psychology, 53,* 1–26. http://dx.doi.org/10.1016/j.cogpsych.2005.10.003

Suls, J., & Wan, C. K. (1987). In search of the false-uniqueness phenomenon: Fear and estimates of social consensus. *Journal of Personality and Social Psychology, 52,* 211–217. http://dx.doi.org/10.1037/0022-3514.52.1.211

Suls, J., Wan, C. K., & Sanders, G. S. (1988). False consensus and false uniqueness in estimating the prevalence of health-protective behaviors. *Journal of Applied Social Psychology, 18,* 66–79. http://dx.doi.org/10.1111/j.1559-1816.1988.tb00006.x

Thompson, A. (2016). *Parallel narratives*. Retrieved from https://news.vice.com/story/journalists-and-trump-voters-live-in-separate-online-bubbles-mit-analysis-shows

Tourangeau, R., Rips, L. T., & Rasinski, K. (2000). *The psychology of survey response*. New York, NY: Cambridge University Press. http://dx.doi.org/10.1017/CBO9780511819322

Townsend, J. T., & Wenger, M. J. (2004). The serial-parallel dilemma: A case study in a linkage of theory and method. *Psychonomic Bulletin & Review, 11,* 391–418. http://dx.doi.org/10.3758/BF03196588

Trevena, L. J., Zikmund-Fisher, B. J., Edwards, A., Gaissmaier, W., Galesic, M., Han, P. K., . . . Woloshin, S. (2013). Presenting quantitative information about decision outcomes: A risk communication primer for patient decision aid developers. *BMC Medical Informatics and Decision Making, 13,* S7. http://dx.doi.org/10.1186/1472-6947-13-S2-S7

Van Rooy, D., Van Overwalle, F., Vanhoomissen, T., Labiouse, C., & French, R. (2003). A recurrent connectionist model of group biases. *Psychological Review, 110,* 536–563. http://dx.doi.org/10.1037/0033-295X.110.3.536

Verduyn, P., Lee, D. S., Park, J., Shablack, H., Orvell, A., Bayer, J., . . . Kross, E. (2015). Passive Facebook usage undermines affective well-being: Experimental and longitudinal evidence. *Journal of Experimental Psychology: General, 144,* 480–488. http://dx.doi.org/10.1037/xge0000057

Weinstein, N. D. (1980). Unrealistic optimism about future life events. *Journal of Personality and Social Psychology, 39,* 806–820. http://dx.doi.org/10.1037/0022-3514.39.5.806

Weinstein, N. D., & Lachendro, E. (1982). Egocentrism as a source of unrealistic optimism. *Personality and Social Psychology Bulletin, 8,* 195–200. http://dx.doi.org/10.1177/0146167282082002

Wojcik, S. P., & Ditto, P. H. (2014). Motivated happiness: Self-enhancement inflates self-reported subjective well-being. *Social Psychological & Personality Science, 5,* 825–834. http://dx.doi.org/10.1177/1948550614534699

Wood, A. M., Brown, G. D. A., & Maltby, J. (2012). Social norm influences on evaluations of the risks associated with alcohol consumption: Applying the rank-based decision by sampling model to health judgments. *Alcohol and Alcoholism, 47,* 57–62. http://dx.doi.org/10.1093/alcalc/agr146

Wood, J. V. (1989). Theory and research concerning social comparisons of personal attributes. *Psychological Bulletin, 106,* 231–248. http://dx.doi.org/10.1037/0033-2909.106.2.231

World Health Organization. (2010). *Global Health Observatory data repository*. Retrieved from http://apps.who.int/gho/data/node.home

Appendix A

Study Descriptions

Study 1

We collected data from a probabilistic national sample of the Dutch population ($n = 1{,}416$; described in detail in Galesic et al., 2012) in July and October 2008. Participants were recruited from the Longitudinal Internet Studies for the Social Sciences (LISS) panel (www.lissdata.nl) and were representative in terms of sociodemographic characteristics for the general population of the Netherlands. They answered questions about 10 characteristics related to their own financial situation, love life, friendships, health, work stress, and education (in randomized order), always using a 7-point fully labeled scale. For instance, one question was "What was the total net income of your household within the last month?" and the answer categories were different ranges of amounts in euros. Text for all questions can be found in Galesic et al. (2012) and the data at http://www.lissdata.nl/dataarchive/study_units/view/54. Taking advantage of the fact that this sample was representative of the Dutch population, we used these self-reports to derive true population distributions. The participants also estimated the distributions of these characteristics in the general population of the Netherlands (estimated population distributions; e.g., "What percentages of adults living in the Netherlands fall into the following categories?"). Finally, 3 months later, the participants were asked to estimate the distributions of the same characteristics in their social circle (social circle distributions; e.g., "What percentages of your social contacts fall into the following categories?"). In this and in all other studies we defined social circle 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."

Study 2

We collected data from a sample of $n = 152$ German participants recruited from the online general public panel developed at the Max Planck Institute for Human Development in Berlin (Galesic et al., 2014) in September and October 2013. Participants (43% female, mean age 41 years, 26% with high school or less, 31% with some college, and 43% with college degree) were asked to complete the same questions about their social circle distributions two (and for some questions three) times, each a week apart. The questions were about political orientation, voting behavior, income, level of stress, education, and number of social contacts.

(*Appendices continue*)

Study 3

We collected data from $n = 50$ participants in the United States, recruited through the crowdsourcing site Mechanical Turk, and $n = 50$ participants in Germany, recruited through the online general public panel developed at the Max Planck Institute for Human Development, in June 2012. Participants (U.S.: 48% female, mean age 37 years, 50% with bachelor's or higher degree; Germany: 52% female, mean age 35 years, 66% with bachelor equivalent or higher degree) first answered questions about 19 of their own characteristics, including questions with four or more answer categories (e.g., education, working hours, personal and household income, frequency of stress, depression, and pain) and with two categories (e.g., whether they had ever experienced theft or had no money for food; whether they believed in a god, attended worship, supported military interventions, and were in favor of acceptance of homosexuality by society). The questions were taken from existing large national surveys that also provided data about answers to each question by probabilistic national samples of general populations of Germany and the United States. Appendix B shows the full text of the questions and their sources. The questions were chosen to cover a range of domains, from those that have an objective answer (e.g., income and education) to more subjective ones (e.g., frequency of stress and pain). We also aimed to include questions that would produce a range of differently shaped distributions, from asymmetrical to symmetrical. Besides providing their self-reports, participants estimated the prevalence of each of these characteristics in their social circles and in the general population of their country.

Questions about social circles and population estimates were asked in two different ways: directly and indirectly. An example of the direct question about the prevalence of different education levels in one's social circle was "When asked . . . 'What is your highest level of education?' . . . what percentage of your social contacts would report a level of education that's lower than yours? ____ %." The indirect question about the prevalence of different education levels in one's social circle was "When asked . . . 'What is your highest level of education?' . . . what percentage of your social contacts would give each of the following answers? Less than high school—high school—junior college—bachelor's—graduate." For questions about population estimates, the words "your social contacts" were replaced with "adults living in the United States" (or "in Germany"). The order of the different types of questions—about self, social circles, population estimates, as well as direct and indirect forms of the latter two types—was randomized for each participant. Within each type of question, the order of the nine characteristics was also randomized. Order of questions did not have discernible effects on any of the results.

Study 4

We collected data from a sample of $n = 104$ U.S. participants recruited from Mechanical Turk (Galesic et al., 2013) in January 2013. Participants (43% female, mean age 34 years, 44% with bachelor's or higher degree) answered three groups of questions about 10 characteristics, ranging from smoking to donating to charity and believing in a god (corresponding to characteristics 1–10 in Appendix B). The questions were taken from publicly available results of large national surveys (e.g., Gallup World Poll). Participants first gave their personal answer to each of the 10 questions. In this way we classified them as either performers or nonperformers on a particular characteristic. Thereafter they estimated the percentage of performers and/or nonperformers in their social circle, and in the general population of the United States. A random half of the participants answered the questions about their social circle first, and the other half about the general population first. For each characteristic, a random third of performers and a random third of nonperformers gave estimates of social circle and population percentages in one of the following response formats: (a) estimating only the percentage of performers, (b) estimating only the percentage of nonperformers, and (c) estimating the percentage of both performers and nonperformers. For more details on the implementation of the study and calculation of different false consensus estimates, see Galesic et al., 2013.

Study 5

We collected data from $n = 100$ U.S. participants from Mechanical Turk in August 2017. Participants first rated the desirability of 113 characteristics on a 7-point scale adopted from the seminal study of Alicke (1985). The instructions were: "We're interested in how desirable or undesirable different characteristics are for the average person. Please rate each characteristic on the scale from *very undesirable* (something that is bad to have) to *very desirable* (something that is good to have)." The items included all of the characteristics used in Studies 1 and 3. For each characteristic, we assessed both its negative end (e.g., "to have low personal income") and its positive end (e.g., "to have high personal income"). This enabled us to calculate relative desirability of each characteristic, $D_{\text{rel}} = D_{\text{pos.end}}/(D_{\text{neg.end}} + {}_{\text{os.end}})$. The items furthermore included three characteristics examined in Kruger and Dunning's (1999) study: the ability to recognize what's funny, the ability to identify grammatically correct standard English, and general logical reasoning ability. For those characteristics too, we asked the participants to rate both a positive end of this characteristics (e.g., "to be able to recognize what's funny") and a negative end (i.e., "to not be able to recognize what's funny"). Finally, the items included 40 items from Alicke (1985), chosen to represent different degrees of desirability (high, moderately high, moderately low, and low) and controllability (low and high). Examples are cooperative (high desirability, high controllability), reserved (moderately high desirability, low controllability), and insecure (low desirability, low controllability). After providing the desirability ratings, the participants completed another short study not reported here.

Data for all studies are available at Open Science Framework (https://osf.io/u97gh/).

(*Appendices continue*)

Appendix B

Materials for Studies 3 and 4

Characteristic	Question text	Original source of both question text and the data for the general population	
		United States	Germany
1. Not having money for food	Have there been times in the past 12 months when you did not have enough money to buy food you or your family needed? Yes–No	Gallup, 2011	Gallup, 2011
2. Donating to charity	In the past month, have you donated money to a charity? Yes–No	Gallup, 2011	Gallup, 2011
3. Experiencing theft	Within the past 12 months, have you had money or property stolen from you or another household member? Yes–No	Gallup, 2011	Gallup, 2011
4. Religion importance	Is religion an important part of your daily life? Yes–No	Gallup, 2011	Gallup, 2011
5. Worship attendance	Have you attended a place of worship or a religious service within the past 7 days? Yes–No	Gallup, 2011	Gallup, 2011
6. God and morality	Which one of these comes closer to your opinion? It is not necessary to believe in God in order to be moral and have good values—It is necessary to believe in God in order to be moral and have good values.	Pew Research Center, 2011	Pew Research Center, 2011
7. Belief in a god	Do you believe in God or a supreme being? Yes–No	Pew Research Center, 2011	Pew Research Center, 2011
8. Smoking	These days, are you smoking any tobacco product at least once a day? Tobacco smoking includes cigarettes, cigars, pipes, and any other form of smoked tobacco. Yes–No	World Health Organization, 2010	World Health Organization, 2010
9. Military force	Do you agree that it is sometimes necessary to use military force to maintain order in the world? Yes–No	Pew Research Center, 2011	Pew Research Center, 2011
10. Homosexuality acceptance	Which one of these comes closer to your opinion? Homosexuality is a way of life that should be accepted by society—Homosexuality is a way of life that should not be accepted by society.	Pew Research Center, 2011	Pew Research Center, 2011
11. Education	What is your highest level of education? Less than high school—High school—Junior college—Bachelor's—Graduate	General Social Survey, 2010	Allbus, 2010
12. Working hours	(Only if part- or full-time employed) How many hours did you work last week, at all jobs? Up to 20.5 hr—21 to 34.5 hr—35 to 39.5 hr—40 to 44.5 hr—45 to 49.5 hr—50 to 59.5 hr—60 or more hr	General Social Survey, 2010	Allbus, 2010

(*Appendices continue*)

Appendix B (*continued*)

Characteristic	Question text	Original source of both question text and the data for the general population	
		United States	Germany
13. Personal income	(In U.S., only if full- or part-time employed who earned some income.) You've mentioned that you earned some income from working last year. In which of these groups did your earnings for last year fall, before taxes or other deductions? Up to $9,999; $10,000$–29,999; $30,000–$49,999; $50,000–$74,999; $75,000–$89,999; $90,000–$129,999; $130,000 or over; rather not say	Behavioral Risk Factor Surveillance System Survey, 2010	Allbus, 2010
14. Household income	In which of these groups did your total family income, from all sources, fall last year before taxes? Up to $9,999; $10,000–$29,999; $30,000–$49,999; $50,000–$74,999; $75,000–$89,999; $90,000–$129,999; $130,000 or over; rather not say	General Social Survey, 2010	Allbus, 2010
15. Political orientation	In politics, people sometimes talk of "left" and "right." Where would you place yourself on a scale from 1 to 7, where "1" means the *extreme left* and "7" means the *extreme right*? Extreme left 1–2–3–4–5–6–7 Extreme right	Translantic Trends Survey, Kennedy, Zsolt, Pierangelo, Philip, & Eichenberg, 2011	Translantic Trends Survey, Kennedy et al, 2011
16. Global warming threat	How serious of a threat is global warming to you and your family? Very serious—Somewhat serious—Not very serious—Not at all serious	Gallup, 2011	Gallup, 2011
17. Stress, worry	How often do you feel worried, nervous, or anxious? Daily—Weekly—Monthly—A few times a year—Never	National Health Interview Survey, Schiller et al, 2010	Allbus, 2010
18. Depression	How often do you feel depressed? Daily—Weekly—Monthly—A few times a year—Never	National Health Interview Survey, Schiller et al, 2010	Allbus, 2010
19. Pain	In the past 3 months, how often did you have pain? Every day—Most days—Some days—Never	National Health Interview Survey, Schiller et al, 2010	Allbus, 2010

Note. Question texts correspond exactly to what was asked in the original sources. Depending on the source, German versions of questions may be slightly different from English versions. Full questionnaires in both English and German are available from the authors.

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