Heuristics, Interactions, and Status Hierarchies: An Agent-based Model of Deference Exchange

Gianluca Manzo[1] and Delia Baldassarri[2]

Abstract

Since Merton's classical analysis of cumulative advantage in science, it has been observed that status hierarchies display a sizable disconnect between actors' quality and rank and that they become increasingly asymmetric over time, without, however, turning into winner-take-all structures. In recent years, formal models of status hierarchies tried to account for these facts by combining two micro-level, counterbalancing mechanisms: "social influence" (supposedly driving inequality) and the desire for "reciprocation in deferential gestures" (supposedly limiting inequality). In the article, we adopt as empirical benchmark basic features that are common to most distributions of status indicators (e.g., income, academic prestige, wealth, social ties) and argue that previous formal models were only partially able to reproduce such macro-level patterns. We then introduce a novel agent-based computational model of deferential gestures that improves on the realism of previous models by introducing heuristic-based decision making, actors' heterogeneity, and status homophily in social interactions. We systematically and extensively study the model's parameter space and consider a few variants to determine under which conditions the macroscopic patterns of interest are more likely to appear. We find that specific forms of status-based

[1] CNRS & University of Paris–Sorbonne, Paris, France
[2] New York University, New York, NY, USA

Corresponding Author:
Gianluca Manzo, CNRS & University of Paris–Sorbonne, Paris, France.
Email: gianluca.manzo@cnrs.fr

heterogeneity in actors' propensity to interact with status-dissimilar others are needed to generate status hierarchies that best approximate these macroscopic features.

Keywords

asymmetric distributions, cumulative advantage, symmetry concern, reciprocity, status inequality, heuristics, homophily, interactions, agent-based modeling, model replication, sensitivity and robustness analysis

Introduction

At least since Weber (1922) introduced his analytical distinction between "class" and "status" (926-40; see, for an historical outlook, Sørensen 2001), the concept of status has been used to refer to the amount of honor, respect, or prestige that an actor is capable to secure within the group to which he or she belongs. In this framework, status hierarchies are conceived as unidimensional rankings of individuals stemming from the crystallization of the myriad of deference gestures that actors exchange in their everyday interactions (Shils 1968). Classical (Merton 1968, 1988) as well as recent research based on mathematical and simulation models (Bothner et al. 2010; Denrell and Liu 2012; Gould 2002; Lynn, Podolny, and Tao 2009) have framed the emergence of status hierarchies as a *self-reinforcing* process driven by mechanisms of cumulative advantage—such as the Matthew effect—in which little qualitative differences between individuals get amplified via deference-conferring gestures (Bask and Bask 2013; DiPrete and Eirich 2006; Rigney 2010; Van de Rijt 2013; Van de Rijt, Kang, Restivo and Patil 2013).

We contribute to this literature by formally modeling and simulating the process through which status hierarchies emerge from micro-dynamics of deference attribution. We add to extant scholarship in three major ways. First, we increase the realism of the behavioral assumptions upon which models of the emergence of status hierarchies are based. In particular, following recent developments in cognitive psychology, we move away from a conception of utility-maximizing actors and model deference gestures according to simple heuristics that are cognitively feasible (Baldassarri 2012:chaps 2 and 3; Manzo 2013). Second, we model patterns of interaction on the basis of more realistic relational assumptions. In particular, drawing from empirical results in network studies and social psychology, we embed

actors' deference exchanges in local interactions with varying degree of homophily (Fiske 2011; Skvoretz 2013). Finally, we try to reproduce, at the macro-level, the basic qualitative features that are common to most status distributions and investigate under which conditions our micro-level assumptions are able to generate such aggregate patterns.

Status and deference attributions are not directly measurable. However, we have substantial empirical knowledge about the bases upon which deference attributions occur. Namely, countless quantitative, survey-based research in sociology (for an overview, see Chan and Goldthorpe 2007; Chan 2010), and experimental studies in social psychology (see Fiske 2010a; Ridgeway 2011) suggest that wealth, income, education, occupation, beauty, cognitive skills, and so on, can all operate as status cues, that is, individual-level characteristics that actors employ to determine how much honor, respect, or prestige a given actor deserves. Our basic assumption is that the distribution of status hierarchies should follow, or even amplify, the qualitative features common to the distribution of these status cues, since deference-conferring gestures are based on them.

Three characteristics stand out as especially important. First, classic as well as contemporary studies consistently show that most of these status proxies, for instance, income and wealth (Chakrabarti et al. 2013; Pareto 1896), academic citations (Eom and Fortunato 2011; Price 1976; Radicchi, Fortunato, and Castellano 2008; Redner 1998), or social ties (Barabási, 2009; Barabási and Bonabeau 2003), have *highly skewed distributions*. While it might be difficult to estimate their specific functional form (Clauset, Shalizi, and Newman 2009; Farmer and Geanaklopos 2008:§ 5), the distribution of these resources is characterized by few individuals with a large amount of resources and a large amount of the population with access to only a small fraction. In several cases, this distributive inequality tends to increase over time, as those individuals who are at the very top tend to disproportionally cumulate more resources, thus increasing the gap with the rest of the population (for income and wealth, see, for instance, Atkinson, Piketty, and Saez 2011; Banerjee and Yakovenko 2012; for citations, see Barabási 2009; DiPrete, Eirich, and Pittinsky 2010).

Second, these distributions are characterized by a gap between actors' "quality," "talent," "merit," or "contribution" and the amount of reward they ultimately get. Classical analyses of academic prizes (see Zuckerman 1977:250) and artists', sportsmen's or liberal professions' earnings (see Rosen 1981; more recently, see Alper and Wassall 2006; Menger 1999), have argued that the gap in terms of recognition, honor, and visibility between recipients of the highest honors or salary and those who receive only modest

rewards is larger than the difference in the quality of their respective performances. Rosen (1981:846) labeled this phenomenon "magnification effect," while Lynn et al. (2009:761) used the concept of "status dispersion" to identify the gap between status hierarchies and the underlying distribution of quality upon which deference-conferring gestures are based.

Third, status hierarchies are likely to be characterized by the coexistence of strong, stable macro-level asymmetry and constant "shifts" in ranks at the micro-level. Although less corroborated by empirical evidence, this pattern of pervasive rank "re-ordering" (or shuffling) in status is explored by Lynn et al. (2009:271) and documented by Van de Rijt, Shor, Ward, and Skiena (2013) in their study of individual fame in media. A similar dynamic has been documented in a study of cities' population (Batty 2006).[1]

In this article, we introduce an agent-based computational model (ABM) of deferential gestures and use it to determine under which conditions the aggregation of myriad of local deference exchanges would lead to the emergence of status hierarchies that present these three macroscopic patterns, namely large, and growing (1) status asymmetry, thus distributive inequality; (2) gap between actors' "quality" (talent or value) and the amount of deference they receive, hence their status position; (3) mismatch between actors' rank in the hierarchy of quality and their rank in the deference-based status hierarchy. We find that a considerable amount of individual-level heterogeneity and specific interaction patterns are needed to generate status hierarchies that best approximate these macroscopic features.

The article unfolds as follows. In the next section, we position our contribution within the vast scholarship on status hierarchies and briefly discuss the merits and limitations of the two micro-founded formal models of status hierarchies that we use as starting point for our own model. Then, we describe and justify our ABM. The third section reports population-level statistics computed on the simulated status hierarchies generated by this model and discusses under which conditions the macroscopic patterns of interest are more likely to appear. We also describe typical status trajectories in order to shed light on the micro-level processes from you which our results originate. We finally discuss the main implications of our study and further developments. (Appendixes A and B, respectively, contain the pseudo-code of our simulation script and the reanalysis of the two previous models that motivated this article).

Formal Models of Status Hierarchies

Within the vast scholarship on status hierarchies (for a recent review, see Lynn et al. 2009:762-68; Podolny and Lynn 2009; Sauder, Lynn, and

Podolny 2012), a first source of inspiration for our study is the research tradition on small groups, namely expectation states theory (Berger, Cohen, and Zelditch 1972; Berger and Fisek 2006; Skvoretz and Fararo 1996) and status construction theory (Ridgeway 2006; Simpson, Willer, and Ridgeway 2013; Troyer 2003; Webster and Hysom 1998). In both approaches, status hierarchies emerge in the context of task-oriented groups and deference attributions are based on expectations about individual performances. Experimental (Ridgeway et al. 2009:46) and computational (Axtell, Epstein, and Young 2001) findings show that small differences in performance, or even initially nonvalued categorical differences among actors, can constitute the basis for biased status beliefs that spread widely throughout a population.

In line with recent developments, we retain the bottom-up, relational perspective of the small-group research tradition, as well as the basic observation of a mismatch between actors' status and their actual quality. However, we frame the problem of the emergence of status hierarchies in more general terms. We do not relate dyadic deferential gestures to task expectations. Instead, we model how actors determine the amount of deference a given actor receives on the basis of general quality and status considerations.

To do so, we follow in the footsteps of Roger Gould's (2002) model of the emergence of status hierarchies as well as its follow-up by Lynn et al. (2009)—LPT (Lynn, Podolny, and Tao model), hereafter. Gould shared with the small-group approach the intuition that "social hierarchies (...) emerge and persist spontaneously rather than by conscious creation, but at the same time without ensuring that rewards exactly reflect differences in individual qualities" (Gould 2002:1146). However, differently from his predecessors, he adopted an initial scenario in which no group task, or preexistent social structures exist but only a small amount of heterogeneity in the distribution of actors' quality. Crux of the model is to explain how initial small differences in quality can turn into an asymmetric status distribution without, however, reaching "radical inequality."

Indeed, following in Merton's footsteps (Merton 1988:606, 610, 617-19), Gould asks how is it possible that status distributions do not evolve into "winner-take-all" distributions in the absence of centralized and institutionalized macro-constraints that would stop the accumulation of resources in the hands of one or a few individuals. Gould's innovative solution is the following: at the micro-level, actors' dyadic deferential gestures are driven, on the one hand, by a social-influence-based mechanism of cumulative advantage according to which actors' deferential gestures are influenced by others' deference attributions and, on the other hand, by a "reciprocity" mechanism

that reflects actors' distaste for unreciprocated deferential gestures. According to Gould, social influence contributes to increase status inequality and the gap between actors' original quality and their final status, whereas the concern for reciprocity limits this growth, thus preventing the distribution of status from resembling a winner-take-all structure.

Although it is difficult to reach an operational definition of winner-take-all inequality (see our discussion in the The model's macroscopic outcomes section; see also Frank and Cook, 1995:3), the way Gould framed the problem of modeling the emergence of status hierarchies as the by-product of *counterbalancing mechanisms* is in line with Merton's original account of the process of "cumulative advantage" in the context of his analysis of the stratification of symbolic rewards in science. More importantly, this breaks with most current scholarship in mathematics, physics, and economics, where formal accounts of the emergence of asymmetric distributions (in particular, power laws) are exclusively concerned with mechanisms triggering inequality growth, whereas no model contains substantive "countervailing processes" (for reviews of this literature, see Andriani and McKelvey 2009:table 2; Farmer and Geanakopotos 2008; Mitzenmacher 2004; Newman 2005).

LPT (2009) maintained the main mechanisms postulated by Gould, but they increased the realism of Gould's model in several ways. First, considering that actors' intrinsic quality is not directly observable, they model dyadic interactions in which actors' intrinsic quality may be under- or overestimated by other actors (ibid:770-71). Second, they move away from Gould's static, equilibrium-oriented perspective, and adopt a dynamic approach, which seems more appropriate, given the goal of explaining the "emergence" of status hierarchies. In their model, actors are involved in a sequence of deference exchanges and they base their behavior on their perceptions of others' most recent behavior (ibid:794-95). Methodologically, LPT (2009:761-62) monitor the macroscopic consequences of the mechanisms postulated at the micro-level using the following two measures: status dispersion—which refers to the potential gap between actors' quality and their status—, and "status re-ordering"—which refers to the potential disjunction between the initial hierarchy of individuals' quality and the final hierarchy of actors' status. Differently from Gould's original study, LPT's analysis is mainly focused on the magnitude of status re-ordering, a form of social construction of status that they regard as more radical than status dispersion (ibid:760).

We take Gould and LPT's model as the basis of our own formal model and improve several of their features. Substantively, three limitations should be highlighted. First of all, both Gould (2002:1153-54) and LPT (2009:769),

although to a different extent, conceive of actors as "computational devices" that maximize a utility function, and the ideal amount of deference that accommodates both actors' desire for interaction with high-status individuals and their distaste for unreciprocated deference attributions is determined relying on a maximization calculus (on this point, see also Chase and Lindquist 2009:584).[2] Second, they build on the simplifying assumption that actors' sensitivity to social influence and to symmetry in deferential gestures is homogenous across the entire population. Third, both Gould (2002:1152) and LPT (2009:773) rest on an oversimplified representation of the social context that amounts to an all-to-all network in which everyone exchanges deference with everyone else.[3]

Three additional problematic aspects concern the method. First, both Gould and LPT perform only a partial numerical analysis of the parameter space over which their respective models are defined, which increases the risk of overlooking anomalies in the model's macroscopic behavior. Indeed, practitioners as well as philosophers of simulation agree that extensive and systematic analysis of the model's parameter space is a necessary condition to assess the robustness of the results (see Helbing and Bialetti 2012, 42, 48, 50; Muldoon 2007; Railsback and Grimm 2011:ch. 23). Second, in both models, the parameter modeling actors' distaste for unreciprocated deferential gestures is positively unbounded (see Gould 2002:1153; LPT 2009:769), thus making a proper numerical analysis of the model even more complicated. Finally, while questions concerning social inequality are clearly at the basis of both Gould's (2002:1149) and LPT's (2009:755-59) models, their analyses lack any quantitative indicator of macro-level inequality: Gould validated his model using social network structures, whereas LPT mainly focused on status re-ordering.

In our view, the combination of these substantive and methodological problems explain why both Gould and LPT drew conclusions concerning their models that are only partially consistent with the actual behavior of these models and especially the behavior of their core mechanisms. Appendix B documents this claim by reporting the results of an extensive numerical reanalysis of both models.

In what follows, we maintain all unproblematic features of Gould and LPT's models, while addressing each of the above-mentioned limitations through a few substantial changes and different methodological choices. Substantively, we increase the realism of the cognitive and relational assumptions of previous models by representing heterogeneous, heuristic-driven actors that are embedded in dyadic interactions with varying levels of status similarity. Methodologically, we theorize the emergence of status

hierarchies using agent-based computational simulations (for a nontechnical introduction, see Macy and Flache 2009; for a comprehensive technical introduction, see Wooldridge 2009), a technique that, despite common mistaken beliefs (see, for instance, Elster 2009:§2), is especially well equipped to combine heterogeneity, network constraints and *decision-making processes that rely on "rule-of-thumb" rather than on maximization principles* (on this latter point, see, among others, Epstein 2006:chaps. 1 and 2; McKenzie 2007; Miller and Page 2004:10; Todd, Billari, and Simao 2005). Finally, compared to previous scholarship, we evaluate under which theoretical conditions our model best approximates the main qualitative patterns that characterize empirical distributions of important status cues such as income, wealth, or social ties on three dimensions of status hierarchies (status dispersion, status reordering, and "status inequality") and assess the extent to which the mechanisms postulated produce the expected macro-level outcomes.

The ABM

Compared to Gould's (2002) model of status hierarchies, which is a classical equilibrium mathematical model with a closed-form analytical solution, and to LPT's (2009) development of Gould's model, which is partly analytical and partly simulation based, our model is computational. Namely, it takes the form of an ABM, that is, a virtual society in which a set of numerical/logical entities (agents) endowed with attributes and embedded in a set of network relationships, are required iteratively and sequentially to interact according to a set of *heuristics*. The model starts from a minimal scenario and evolves according to a set of empirically and experimentally grounded behavioral rules that drive micro-level dyadic deferential gestures (see, respectively, sections Model initial state and Model dynamic). To help the reader, Table 1 provides an overview of the model's variables and Appendix A summarizes the overall simulation script.[4]

Model initial state. We start with a idealized setting in which N agents i (with $i = 1, \ldots, N$) are embedded in a full network and are assigned the following attributes: (1) intrinsic quality (Q_i), (2) error e_{ij}, which captures agent i's error in assessing agent j's intrinsic quality Q_j, (3) propensity to interact with status-dissimilar others (h_i), (4) propensity to imitate other deferential gestures (w_i), and (5) sensitivity to the difference between the given/received amount of deference in dyadic encounters (s_i). As the subscript i suggests, differently from previous models, each of these attributes may vary across agents, thus allowing for the study of individual-level *heterogeneity*.

Table 1. List of Symbols/Variables used in the Agent-based Model.

Symbol	Variable	Short Label	Value
Q_i	i's intrinsic quality	Quality	$N \sim (0,1)$
e_{ij}	Error i makes in assessing j's intrinsic quality Q_j	Quality misperception	$N \sim (0,1)$
w_i	i's propensity to imitate other deferential gestures	Imitation	$U \sim (x, y)^a$
s_i	i's sensitivity to the difference between the given/received amount of deference in dyadic encounters	Symmetry/ Reciprocity	$U \sim (x, y)^a$
h_i	i's propensity to interact with status-dissimilar others	Heterophily	$U \sim (x, y)^a$
q_{ij}	i's perception of j's quality	Quality perception	Equations (1) and (5)
a_{ij}	amount of deference i direct to j	Attachment	Equations (2) and (6a/b)
ddd_{ij}	Difference between a_{ij} and a_{ji}	Attachment difference	Equations (6a/b)
S_i	i's status	Status	Equations (3) and (7)
SR	Difference between the highest and the lowest values of agents' status S_i	Status range	Equation (4)
SD_{ij}	Difference between i's and j's status	Status dissimilarity	Equation (4)

Note: [a]The model analysis will consist in extensive and systematic variations of "w," "s," and "h." For this reason, we will often refer to these variables as "(core) parameters." The lower/upper limits of the respective uniform distributions will depend on simulation scenarios (but $x \geq 0$ and $y \leq 1$ will always hold; see endnotes 13, 16, and 17).

Agent's intrinsic quality Q_i is assumed to follow a normal distribution with mean equal to 0 and standard deviation equal to 1. In very abstract terms, Q_i represents the value, merit, talent, or "competence" of a given actor. The model is purposely silent about the source of agents' intrinsic quality. As we suggested in the introduction, one possibility is that actors rely on more easily observable features like education, income, beauty, or academic prestige to infer others' intrinsic quality. All that matters for us is the fact that this intrinsic quality Q_i constitutes the starting point of a complex cognitive process of deference attribution.

At the outset, the process of deference attribution is driven by two simple mechanisms that are sequentially applied within each possible dyadic interaction. First (equation [1]), agent i's perception of agent j's quality (q_{ii}), is

defined as agent j's intrinsic quality Q_j plus some noise (e_{ij}). Since intrinsic quality cannot be observed directly, this "error term" introduces the possibility that agent j's intrinsic quality is under- or overestimated. Second (equation 2), agent i uses this perception q_{ij} of j's quality to assign j an amount of deference a_{ij} proportional to q_{ij} ("a" stands for "attachment," the term that both Gould and LPT used to denote the amount of deference exchanged by two actors).

$$q_{ij} = (Q_j + e_{ij}), \text{with } e_{ij} \sim N(0,1) \tag{1}$$

$$a_{ij} = q_{ij} \tag{2}$$

Thus, at the outset, the process of deference attribution is extremely simple. Each dyadic deference attribution reflects the perception of quality, high-quality actors receiving more deference than low-quality actors. The only factor altering the perfect correspondence between the distribution of agents' intrinsic quality and the resulting status hierarchy is the quality misperception term e_{ij}. After all deference gestures have been exchanged, the status S_i of each agent i is calculated as the average of all deference attributions received (equation [3]); (the average being computed on $N - 1$ agents because self-deferential gestures are not permitted).

$$S_i = \frac{1}{N-1} \sum_{j \neq i} a_{ji} \tag{3}$$

This initial scenario, which, except for the use of the mean instead of the sum in the status aggregative function, follows LPT's model, is intended to mimic empirical settings in which participants in a small group (e.g., a business meeting, a conference, a party, a sport team), who have had no or only a few opportunities to interact with each other, base their deference attribution on quick, more or less superficial, assessments of others' quality. Methodologically, this highly idealized scenario has the advantage of creating a largely neutral starting point in which the distributions of quality and status are very similar. This scenario, in fact, will make it possible to assess whether, and under which conditions, our model's dynamic is indeed capable of producing a disconnect between the initial distribution of intrinsic quality and the final distribution of status.

Model dynamic. After the artificial world is initialized, the model's dynamic consists of the following sequence of events: (1) each agent determines the set of agents with which he accepts to interact ("partner selection"); (2) each

agent makes up his or her mind about the partner's quality ("quality perception"); and (3) partly on this basis, each agent decides the amount of deference the partner should receive ("deference attribution"). Finally, (4) the status of each agent is computed ("status update"). Each model's iteration consists of randomly invoking every agent and sequentially executing these four algorithms.

Step 1. Partner selection: The "sirens" heuristic. Whereas Gould's (2002) and LPT's (2009) model assume that dyadic deference exchanges occur between all actors, in our model we do take into account the level of *status dissimilarity* SD_{ij} that exists between every pair of actors and make their likelihood of interacting dependent on it (equation [4]). Our assumptions are justified on the basis of extensive empirical and experimental evidence.

Countless empirical studies of real-world social networks show a tendency to associate with others on the basis of economic, political, and cultural similarities (Blossfeld 2009; DiPrete et al. 2010; McPherson, Smith-Lovin, and Cook 2001; Skopek, Schulz, and Blossfeld 2011). Even in small-group settings, where one may expect lower assortative mixing, there is, in fact, strong status-based homophily (Barrat et al. 2010).[5] From this evidence, we conclude that settings in which individuals turn a blind eye to status considerations are quite rare.

Drawing on valuable insights from psychology, we model a partner selection process that incorporates actors' preference for status similarity. Indeed, both high- and low-status actors may have good reasons for isolating themselves in order to minimize their exposure to unpleasant psychological experiences (Fiske 2010b, 2011; Skvoretz 2013). On the one hand, high-status people may react with "scorn" (Fiske 2010b:698) to interactions with low-status individuals: they may feel guilty, or, alternatively, annoyed by (what they consider) bad manners and/or poor reasoning. Finally, they may even consider proximity with low-status people a threat to their own social image (e.g., see Podolny's [2005:37] argument on "status leaking"). On the other hand, low-status people may experience envy, anger, and a feeling of inadequacy when they relate to high-status people. In addition, emotions associated with asymmetric social comparisons tend to generate specific beliefs (Fiske 2011:ch. 1 and 2): low-status individuals are perceived as less warm, competent, intelligent, and, in short, less typically human, on the other hand, high-status individuals are perceived as cold and calculating, even though they are competent.

For all these reasons, interactions among status-dissimilar actors are likely to reduce the amount of respect between them. And, as experimental

evidence suggests, people dislike being disrespected. Even though actors clearly have different preferences for rank positions, "individuals more uniformly prefer being respected and held in higher regard to being disrespected and held in contempt" (Anderson et al. 2012:1086).

Both actor's concern for the corrupting emotions that might be triggered by a comparison with status-distant actors as well as their distaste for lack of respect, leads us to assume that actors, although in principle may desire to interact with socially distant actors, in practice, prefer to protect themselves against unpleasant psychological experiences, and therefore tend to restrict the pool of others with whom they are willing to interact to status-similar others. Like "Ulysses binding himself to the mast so that he would be unable to respond to the song of the Sirens" (see Elster 2007:241), in our model agents are allowed to restrain themselves from interacting with alluring others whose response is likely to hurt them, thus exchanging deference only with a subgroup of *alters* who are within a subjectively defined acceptable status range.

We represent the "sirens" heuristic, according to which individuals tend to exchange deference gestures with status-similar others, by computing, for each agent, the *status dissimilarity*, SD_{ij}, between him or her and any potential *alter j*, and, then, establishing if this difference falls within an acceptable status dissimilarity. To take into account changes in the distribution of status over time, the acceptable status dissimilarity depends on two elements: first, a population-level "status range," SR, which, in any given iteration t, is common to all agents and is computed as the difference between the highest and the lowest values of agents' status S_i, and, second, an agent-level parameter of heterophily (h_i), which expresses the agent's propensity to interact with status-dissimilar others.[6]

$$\text{if}(-h_i \times SR_t \leq SD_{ijt} \leq h_i \times SR_t) \rightarrow i \text{ interacts with } j, \qquad (4)$$

with : $h_i \sim U[x, y]$, (see Table 1); t(current iteration) = 1(first iteration), ... , T(last iteration);

$$SR_t = |\text{Highest}(S_{it}) - \text{Lowest}(S_{it})|,$$

$$SD_{ijt} = S_{it} - S_{jt}.$$

This "filtering" mechanism allows to model a great variety of interaction patterns. When $h = 1$ for all agents, we fall within the all-to-all network world postulated by Gould (2002) and LPT (2009). By contrast, for values of h close to 0, we enter a scenario in which deference exchanges take place within status homogeneous dyadic encounters.

By modeling heterophily as an individual-level attribute, we can also let it vary across agents, thus introducing heterogeneity with respect to actors' reluctance to interaction with status-dissimilar others. In particular, in a specification of the model, we make agents' propensity to interact with dissimilar others contingent on agent's status itself and study the macroscopic consequences of a scenario in which low-status actors have high tolerance for interactions with high-status actors (see section on Status Hierarchies in Artificial Heterogeneous Societies). This scenario is intended to capture the tension between actor's propensity to establish social relations with persons of comparable status and their aspiration to interact with higher-prestige actors, as documented by modern social stratification research (see Laumann 1965). Social network studies have also shown that unreciprocated friendship nominations disproportionately involve low-status actors that claim friendship with high-status actors, which may well reflect aspirational, status-seeking behaviors (see Ball and Newman 2013).

Step 2. Quality perception: The "imitation" heuristic. Following partner selection, agent i is required to assess the quality of each selected partner. In the real-world, this is not an easy task, since the intrinsic quality of an actor is not visible to others. It seems therefore plausible to assume that actors' inferences about others' intrinsic quality may be affected by errors of under-/over-estimation (see equation 1) and, moreover, that actors would rely on cognitive shortcuts based on contextual cues. Among these cues, a prominent role is played by other people's behavior, namely the deferential gestures that other actors give to the actor in question.

Several elements support this assumption. In general, especially under conditions of uncertainty, actors rely on others' behavior as a source of information, a phenomenon that Hedström (1998) labeled "rational imitation." Formal models have also shown that "public" information can, under certain conditions, even overpower "private" information (see Bikhchandani et al.'s (1992) classical work on "information cascades"). The fact that actors frequently follow others' behavior is supported by a large amount of experimental evidence in social psychology, where this phenomenon is called "social validation" (see Cialdini and Trost 1998:171, 172) or "social proof" principle (See Cialdini 1984:ch. 4). More recently, the so-called fast-and-frugal heuristic research program in cognitive psychology (for an overview, see Gigerenzer and Gaissmaier 2011) has advanced the idea of 'social heuristics', that is, strategies relying on others' behavior to handle choice settings characterized by uncertainty (for an overview, see Hertwig and Herzog 2009:680-690). In

particular, when the "environment is stable or only change slowly, info search is costly or time-consuming," individuals tend to rely on imitation heuristics such as "imitate-the-majority" or "imitate-the-successful" (Gigerenzer and Brighton 2011:17). Finally, experimental studies on reputation show that receiving positive information on a given actor from a third party increases the likelihood of considering such actor trustworthy in subsequent interactions (see Buskens and Raub 2002; Barrera and Buskens 2007). This effect seems to stem from imitation rather than learning (see Barrera and Buskens 2009).

$$q_{ij} = (Q_j + e_{ijt}) + w_i \times S_{jt-1}, \tag{5}$$

with : $e_{ij} \sim N(0,1)$; $w_i \sim U[x, y]$ (see Table 1); t (current iteration) = 1 (first iteration), ... , T (last iteration); S_j given by equation (7).

These empirical regularities inform the way in which agents' perception of others' quality is modeled. The first part of equation (5) states that agent i's perception of j's quality is proportional to j's intrinsic quality (Q_j) plus some error (e_{ij}), which represents quality misperception due to its unobservable nature (similarly to what happens at the outset, see equation 1). The second part of equation (5) formalizes the imitation heuristic, that is, as interactions unfold, to assess j's quality agent i also relies on the status S_j that j has secured within the group during the previous iteration (or at the outset, in the first iteration) thus agent i relies on others' deferential judgments. In particular, the second term of equation (5) builds on an "average rule" (Hertwig and Herzog 2009:683, 684, 686) to represent an imitate-the-majority heuristic (Gigerenzer 2008, 31; Gigerenzer and Brighton 2011:17), that is, a cognitive shortcut according to which agents' judgments tend to follow the central tendency (i.e., the mean) of the distribution of deferential gestures. Modeling social influence through this heuristic leads to a cumulative advantage dynamic, in which the higher/lower an agent's status is at time t, the larger/smaller the probability that the perception of his or her quality will be even more positive/negative at $t + 1$.

The parameter w_i determines the strength of the imitation heuristic: an agent's propensity to imitate other deferential gestures is greater as w tends to 1. However, since the sensitivity to social influence is implemented at the agent level, population heterogeneity can be introduced and agents' sensitivity to social influence can be modeled as an endogenous trait depending on agents' status itself (see section on Robustness Checks).[7]

Step 3. Deference attribution: The "sour grapes" heuristic. After having defined the quality of its interaction partners, agent i has to determine the

amount of deference a_{ij} that, to his or her eyes, each agent j should receive. To model this micro-level gesture, we rely on Gould's (2002:1149) intuition that "it is painful to pay attention to another person if the favor is not repaid." Thus, we assume that the amount of deference that a given actor is willing to give an alter is partly driven by a concern for reciprocation. Actors interpret unreciprocated deferential gestures as a sign of disrespect and, since they value being respected (Anderson et al. 2012), they are hurt by the lack of symmetry.

We formally represent this argument with equation (6a) and (b). In each dyadic deferential exchange, our agents follow a simple behavioral rule. First, they have to compute the "difference in dyadic deference" ddd_{ij} between the amount of deference a_{ij} that agent i gave to agent j and the amount of deference a_{ji} that i received from j in their last encounter. Then, according to the value of this difference, they decide the amount of deference a_{ij} deserved by the current partner. In particular, as stated by equation (6a), when ddd_{ij} is null or negative, meaning that the focal agent i has received the same or more deference than he or she gave to j, i assigns to j an amount of deference proportional to the perception he or she has of j's quality (similarly to what happens at the outset, see equation 2). In this case, indeed, the agent's need of being respected is satisfied. By contrast, equation (6b) tells us that, when ddd_{ij} is positive, meaning that the focal agent i has given j more deference than he or she has received from j, i reacts by subtracting an amount of deference that is proportional to the excess of deference he or she gave j from the amount of deference that he or she gives j on the basis of his or her perception of j's quality (q_{ij}). Since agent's need for respect is violated, he or she overreacts by punishing nonreciprocators.

$$\text{if } ddd_{ijt-1} \leq 0 \rightarrow a_{ijt} = q_{ijt}, \tag{6a}$$

$$\begin{aligned} \text{if } ddd_{ijt-1} > 0 \rightarrow a_{ijt} = q_{ijt} - s_i \times ddd_{ijt-1}, \\ \text{with : } s_i \sim U[x,y] \text{ (see Table 1)} \end{aligned} \tag{6b}$$

$$\text{With : } q_{ijt} = \text{equation (5) and } ddd_{ijt-1} = a_{ijt-1} - a_{jit-1}.$$

Thus, equation (6a) and (b) represents Gould's assumption that deferential gestures are driven by a concern for symmetry. However, differently from previous work, we model this concern as a simple cognitive heuristic following the logic of a sour grapes mechanism (see Elster 2007:35, 48). In particular, we assume that actors, instinctively, or even unconsciously, react to

deferential gestures as Aesop's fox. As long as *ego*'s partner is equally or even more deferent toward *ego* than *ego* is to him or her, *ego* would honestly assess the amount of deference to confer upon his or her partner, basing his or her consideration on his or her perception of the partner's quality (see equation 6a). By contrast, when *ego* is more deferent to his or her partner than the latter is to him or her, *ego*'s desire for respect goes unfulfilled, and he or she reacts by changing the amount of deference his or her partner receives. Namely *ego* applies a deference penalty which is proportional to the excess of deference *ego* attributed to his or her partner in their last encounter (see equation 6b). As in Aesop's fable, in our model of deference exchanges, the value subjects confer to an object (i.e., the deference *alter* receives) is not only determined by its real value (i.e., *alter*'s perceived quality) but also by their capacity to benefit from it (i.e., receiving congruous deference attribution from *alter*).

Finally, as with other core parameters, this concern for symmetry in deference exchanges is modeled at the agent level through parameter s_i, thus allowing for individual-level variation in the intensity of the sour grapes heuristic. Namely, agents with $s_i = 0$ are not concerned with being reciprocated, and their deferential gestures are exclusively based on their quality perceptions. By contrast, agents with $s_i = 1$ are maximally sensitive to asymmetries in deference attributions and determined to sanction even the smallest difference in dyadic deference. In some variants of the model, we even make the concern for symmetry endogenous to agents' status itself. Namely, we assign low sensitivity to unreciprocated deference attributions to low-status actors in order to capture the fact that low-status individuals may be particularly interested in pursuing high-status actors and therefore more willing to accept the psychological costs of having their status attributions go unreciprocated (see section on Robustness Checks).

Step 4. Status update: The "averaging" heuristic. After all deferential gestures have been exchanged, the last step of the model's dynamic requires the computation of each agent's status and the consequent status hierarchy at iteration *t*. While Gould (2002) and LPT (2009) models compute status as the sum of all status attributions an agent has received, we rely instead on a "(temporally weighted) averaging heuristic" that takes into account the contextual cues that real-world actors use.

Experimental evidence on the widespread use of the availability and the anchoring heuristics (see Gigerenzer and Gaissmaier 2011) suggests that actors, when estimating certain properties, rely on contextual cues that are cognitively accessible and salient. In our case, we assume that the estimation of actors' overall status is affected by (1) deferential gestures of similar size that occur quite

frequently, (2) deferential gestures that occur rarely and are extraordinary high or low, and (3) deferential gestures that occurred more recently.

The specific form of averaging heuristic we propose is formalized in equation (7) in which we take the average of all the deference gestures a_{ij} received by a given agent. In particular, we exploit two basic properties of the average measure—that is, its capacity to capture the central tendency of a distribution and its sensitivity to extreme values—in order to capture the consistency of deferential gestures across all the "evaluators," and to take into account particularly positive/negative deference attributions (for experimental evidence on the averaging heuristic, see Soll and Larrick 2009). Finally, we model the intuition that more recent deferential gestures are cognitively salient, by making them count more in agents' perception of others' status. This is achieved by weighting each deferential gesture for the ratio between the iteration (t^*) in which it was received and the current iteration (t). Namely, the more remote a deferential gesture is, the less important it is.[8]

$$S_{it} = \frac{1}{N-1} \sum_{j \neq i} \frac{t^*}{t} a_{jit*} \tag{7}$$

With:

    t (current iteration);

    t^* (iteration during which the deference attribution a_{ij} was received);

    both t and $t^* = 1$ (first iteration), ..., T (last iteration);

    $t^* \leq t$

The model's macroscopic outcomes. Conceptually, the basic logic behind the formal model described so far is simple. While social influence, in the form of an imitation heuristic, should trigger a "rich-get-richer" dynamic, thus a greater gap between agents' quality and their final status as well as higher status inequality, *ego*'s concern for symmetry and the deference penalties given to *alters* that do not reciprocate should trigger a "rich-get-less-rich" dynamic that counterbalances the effect of the first heuristic. Although the models' details differ, these were precisely the theoretical expectations formulated by Gould (2002:1146, 1149) and LPT (2009:766).

However, as our reanalysis of Gould's (2002) and LPT's (2009) model suggests (see Appendix B), and the analysis of our own model will confirm in greater detail, the population-level consequences of social influence and symmetry concern are less univocal than one may expect. These consequences, indeed, depend on the specific way these mechanisms are modeled and on the specific measures one adopts to monitor their macroscopic

outcomes. Thus, the formulation of ex-ante facto theoretical expectations should not be entertained lightly.[9]

For this reason, we do not evaluate our model in relation to a set of a priori theoretical expectations concerning the effects of the core mechanisms. Our benchmark is instead the macroscopic regularities, discussed in the introduction, which are distinctive of the distribution of many "status cues" such as income, wealth, or social ties. Our aim is to assess the conditions under which the formal model presented in the previous section generates the qualitative form of these macro-level patterns. Namely, we study the macroscopic behavior of the simulation model using three indicators.

First, to assess the extent to which our model generates an increasing gap between agents' quality, talent, or value and the status position they achieve, we follow LPT (2009:775) and compute the average absolute difference between the status each agent reaches at the end of a given iteration t (S_{it}) and his or her intrinsic quality Q_i at the outset (equation [8])—this measure will be referred to as status dispersion or "status–quality gap."

$$\text{StatusQualityGap} = \frac{1}{n}\sum_{i}^{n}|S_{it} - Q_i| \qquad (8)$$

Second, to assess the extent to which our model generates a growing mismatch between actors' rank in the hierarchy of quality and their rank in the deference-based status hierarchy, we follow LPT (2009:773) and compute the Spearman's rank correlation coefficient between the agent's rank in the hierarchy of intrinsic quality at the outset (R_{Q_i}) and the agent's rank in the hierarchy of status at the end of a given iteration t ($R_{Q_{it}}$; equation 9)—hereafter, we will refer to this measure using either the statistical label (ρ) or the expression "status–quality re-ordering."

$$\text{StatusQualityReordering} = 1 - \frac{6\sum_{i=1}^{n}(R_{Q_i} - R_{S_{it}})^2}{n^3 - n} \qquad (9)$$

Finally, to assess the extent to which our model generates increasing inequality in the distribution of status, we follow well-established practices in the study of asymmetric distributions such as income and wealth and compute the Gini coefficient of the distribution of agents' status at the end of a given iteration t. A Gini of 0 corresponds to absolute equality, while a Gini of 1 represents a winner-take-all scenario.

As mentioned before, previous authors have described status hierarchies as tending toward winner-take-all inequality without never reaching it (Gould 2002:1149), but they did not use a direct indicator of distributive

inequality in order to assess whether the mechanisms they postulate actually generate this trend. The Gini coefficient is not always an appropriate measure to detect a hidden cumulative advantage mechanism (see Bask and Bask 2003; Van De Rijt 2013). However, when the measure of Gini is applicable, a deep relation exists between its value and the degree of asymmetry of the underlying cumulative probability distribution (see Giorgi and Nadarajah 2010; Yitzhaki and Schechtman 2013:ch. 5) and trends in Gini can be used as an indicator of how much asymmetric, thus concentrated, the distribution of a given resource has become (see, for instance, Dragulescu and Yakovenko 2001a, b; Newman 2005:section 3.4). For this reason, we rely on it to study the population-level consequences of our model in terms of status inequality.[10]

Results

The four-step model described in section Model Dynamic was simulated for an artificial population of 30 agents over 100 iterations (2,000 for robustness checks). This choice facilitates the comparison with previous models while substantially extending the time window the model's behavior is monitored (LPT 2009:772 study 30 agents but limit themselves to 20 iterations). In this section, we report on the simulated trends of our three outcomes of interest, the status–quality gap, status–quality re-ordering, and Gini. In addition, to shed light on the micro-level dynamics from which these population-level trends emerge, we also analyze typical agent-level status trajectories. We first consider a scenario in which core attributes are distributed homogeneously across the agents and then move to consider scenarios that incorporate individual-level heterogeneity. In brief, we find that the variants of the model in which we assume status-dependent forms of agent heterogeneity bring about aggregate behavior more in line with the empirical patterns of real-world distributions.

Status hierarchies in artificial homogenous societies. First, we study a scenario in which all three individual-level attributes are homogenous across agents (and stable over time), that is, all agents have the same propensity to interact with status-dissimilar others (heterophily, h), the same propensity to imitate others' deferential gestures (imitation, w), and the same sensitivity to deferential differences in dyadic encounters (symmetry, s). We sampled the entire parameter space by simulating over the entire range of each parameter (from 0 to 1 for "w" and "s," and, from 0.1 to 1 for "h") considering 0.1-unit changes. We analyzed the model's behavior over 1,210 parameter combinations; each parameter combination was replicated 100 times to assess the variability of the model's outcomes due to its stochastic elements.[11]

Figure 1 visualizes the evolution over 100 time periods of our three measures of interest under the assumption of "homogeneity." To increase readability, the figure only shows simulated trends for extreme values of agents' sensitivity to imitation (w) and symmetry in deference (s), and for low ($h = 0.1$), intermediate ($h = 0.5$), and high levels ($h = 1$) of heterophily.

Let us consider the status–quality gap (upper panel). First, results show that, under various combination of parameters, the more agents' imitate others' deferential judgments (black plots, $w \rightarrow 1$), the greater, on average, the disconnect over time between agents' status and their initial quality. Second, as heterophily increases ($h \rightarrow 1$), thus agents are more likely to experience status-distant encounters, the status–quality gap is smaller and grows more slowly, and the effect of imitative behaviors ($w \rightarrow 1$) is weaker. Third, variation in symmetry, namely greater intolerance to unreciprocated deference attributions ($s \rightarrow 1$), does not actually counterbalance, in the aggregate, the effect of social influence.

Results for the measure of status–quality re-ordering are murkier (central panel). In particular, the effect of imitation ($w \rightarrow 1$) is visible only in a world of strong heterophily ($h \rightarrow 1$), and it goes in the direction of greater, not lower, coherence between quality and status hierarchies. Whereas greater concern for symmetry ($s \rightarrow 1$) leads to more frequent reshuffling of agents' quality/status rank.

Finally, we observe contrasting trends with respect to the Gini coefficient (bottom panel). Imitation ($w \rightarrow 1$) leads to high levels of status concentration (with Gini oscillating around relatively high values, i.e., 0.45) only when all agents strongly value status similarity ($h = 0.1$), while as we simulate more heterophily-oriented agents ($h = 0.5$, for instance), the effect of imitation becomes weaker, and it disappears under the all-to-all network condition ($h \rightarrow 1$). The same holds for the counterbalancing effect of symmetry concern.

To determine the general character of these results, we run linear regression for each of the status measures on the entire set of 1,210 parameter combinations (Table 2, panel A). While the plots described previously well visualize the nonlinear nature of the major population-level consequences of our model, we rely on the linear approximation of regression models to test the extent to which the aggregate effects can be generalized *across the entire parameter space* (for this kind of regression-based sensitivity analysis, see Fararo and Butts 1999:51-52; see Leombruni and Richiardi 2005, in agent-based modeling, see Railsback and Grimm 2011:287; and see Saltelli, Chan, and Scott [2000] 2008:24-25, 123-26, 280-82; for a discussion of it in economics).
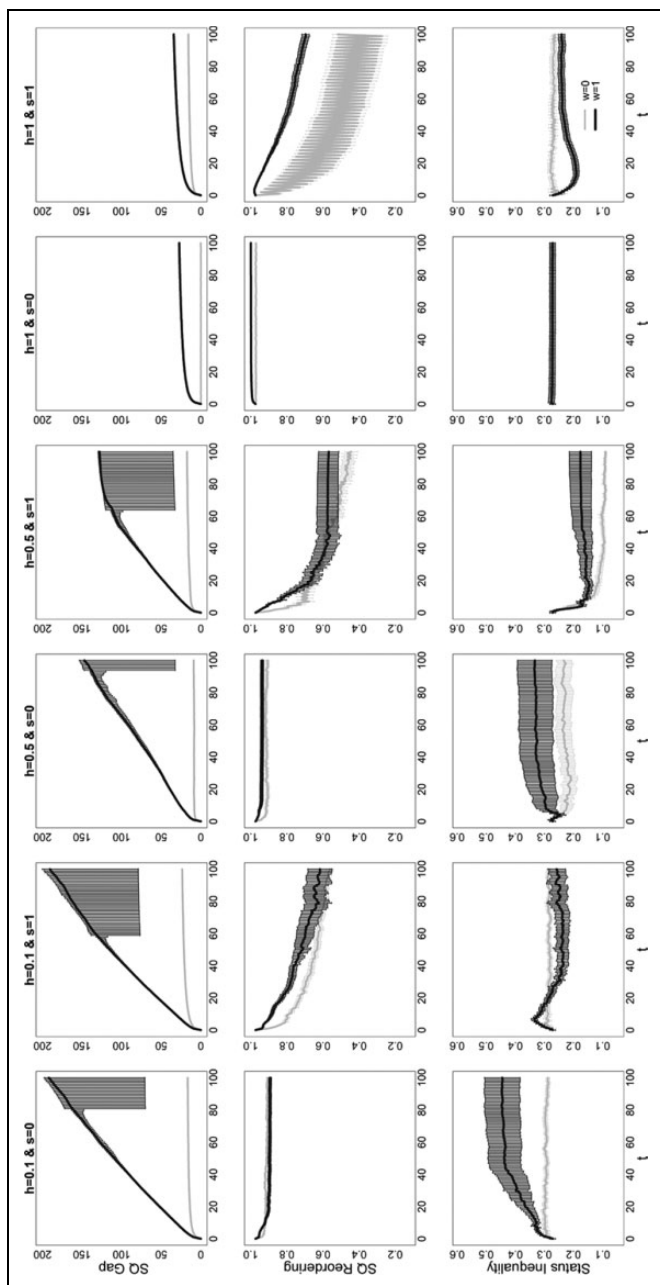
Figure 1. (Experimental condition: agents are homogenous on all core parameters). Evolution of the simulated values of Status–Quality gap (decibel scale; top panel), Status–Quality re-ordering (p; central panel), and status inequality (Gini; bottom panel) over 100 iterations (x-axis) as a function of agents' imitation propensity (w; lines), heterophily (h), and symmetry (s; columns). Values are averaged across 100 replications for each parameter combination and time period (whiskers for 95 percent confidence intervals). $N = 30$ agents.

Table 2. Ordinary Least Squares Regression Analysis.

	Status–quality Gap		Status–quality Re-ordering		Gini	
A, Homogeneity world						
	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	23.667***	2.179	1.005***	0.007	0.304***	0.004
h	−90.169***	2.198	0.1270***	0.007	−0.123***	0.004
w	155.364***	1.9962	−0.004	0.006	0.017***	0.004
s	27.812***	1.996	−0.328***	0.006	−0.088***	0.004
e	−0.380***	0.316	−0.072***	0.001	−0.003***	0.001
B, Status-based heterogeneity world (on h)						
	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	5.132	5.986	1.190***	0.032	0.579***	0.031
w	186.650***	6.384	−0.274***	0.034	0.071**	0.033
s	−18.667**	6.384	−0.470***	0.034	−0.283***	0.033
e	−2.687*	1.090	−0.074***	0.006	−0.018**	0.006

Note: Estimates for heterophily (h), imitation (w), symmetry (s), and quality misperception (e). The units of analysis are the 2,420 (for panel A) and 72 (for panel B) parameter combinations under which the models were simulated. For each of them, we computed the average value of the variables of interest over 100 replications at the 100th iteration.

Table 2 (panel A) shows that (1) agents' sensitivity to imitation (w) has a positive net effect on the amount of both status–quality gap and status concentration observed in our virtual worlds. Instead, there is no general, net effect with respect to status–quality re-ordering. (2) Agents' concern for symmetry—thus the intensity of the sour grapes heuristic—, has a negative net effect on status–quality re-ordering and status concentration but a positive net effect on the amount of status–quality gap. Finally, (3) agents' heterophily, thus their tolerance for status-dissimilar interactions has a negative net effect on status–quality dispersion and on status concentration but a positive net effect on status–quality re-ordering.[12]

Two main conclusions can be drawn from these results. First, under the assumption of agents' homogeneity (on h, w, and s), the core mechanism of cumulative advantage, based on the imitation heuristic, and its counterbalancing mechanism of symmetry concern, based on the sour grapes heuristic, do not have univocal macroscopic effects. In particular, the former generates more status–quality gap and more status concentration over time (even though Gini values are not particularly high), but it does not have a similar effect on status–quality re-ordering. By contrast, the latter works as a counterbalancing force only with
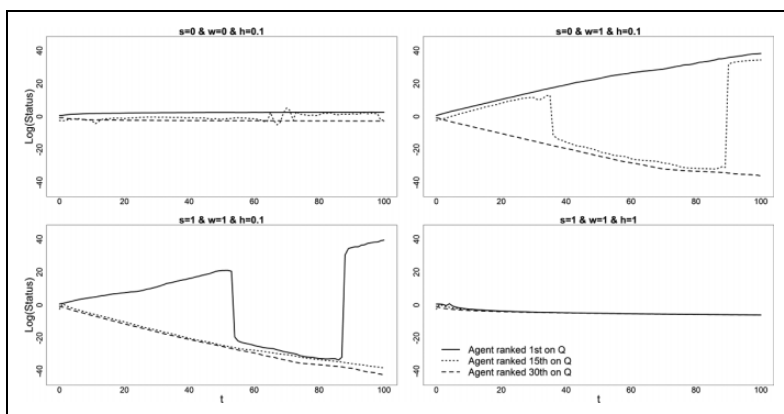
Figure 1a. (Experimental condition: agents are homogenous on all core parameters). Evolution (over 100 iterations, x-axis) of the status (y-axis) of the agents ranked 1st, 15th, and 30th on the exogenous hierarchy of the intrinsic quality Qi. For each agent, status values are averaged over 100 replications of the model and they are plotted on a logarithmic scale.

respect to status concentration, while it enhances the status–quality gap and status–quality re-ordering rather than containing them. Second, agents' propensity to interact with status-dissimilar agents (h) plays a crucial role in the model's dynamic. On the one hand, as visible from the regression results, this is the only feature that has univocal effects on the three outcomes of interest: the more we approximate an all-to-all network scenario (i.e., when "h" increases), the smaller the gap between quality and status (in terms of both their absolute value, i.e., status–quality gap, and of rank distribution, i.e., status–quality re-ordering), and status concentration, that is, Gini coefficient. Before we turn to different scenarios, let us better understand the micro-level dynamic underlying these aggregate patterns.

Status trajectories in artificial homogenous societies. Figure 1a shows the status trajectories of three typical agents. The graph in the upper-left corner shows that, when agents interact locally ($w = 0.1$) and are virtually insensitive to both symmetry concern and imitation ($s = 0$ and $w = 0$), their status varies but no rich-get-richer dynamic appears. By contrast, as the plot in the upper-right corner suggests, when social imitation is maximal ($w = 1$), small quality differences at the outset turn into increasingly large status differences over time. Maximal concern for symmetry ($s = 1$) mediates this effect (bottom-left corner): in fact, the status trajectories of medium- and

low-quality agents are closer to each other, whereas high-quality agents continue to achieve greater status, although more irregularly. Finally, full convergence in status trajectories is reached under the condition of maximum heterophily, in which each agent interacts with everyone else ($h = 1$).

To explain the numerical origin of the equalizing effect of heterophily ($h \rightarrow 1$), let us consider the simplified scenario in which there are only three artificial agents with the following status at the outset: $A0 = 0.05$, $A1 = 1.25$, and $A2 = 1.12$. Let us also imagine that there is no random reassignment of intrinsic quality at each iteration (i.e., the first term of equation 5 is absent), agents are fully sensitive to social influence ($w = 1$), and they are insensitive to unreciprocated deferential gestures ($s = 0$). Under these assumptions, when each of the three agents interact with everyone else ($h = 1$), the combination of equation (5) and (6a/b) leads to the following dyadic attachments a_{ij}: A0 = (0.05, 0.05), A1 = (1.25, 1.25), and A2 = (1.12, 1.12). As a consequence, since the status of each agent is computed as the mean of the attachments received (see equation [7]), each agent will end up with the same status as at the outset. By contrast, if A0, A1, and A2 are not forced to interact with everyone else ($0 < h < 1$), this vicious loop is interrupted because there will be no longer perfect correspondence between the set of attachments received at time t and those received at time $t + 1$.

This scenario never fully occurs in our simulations because quality perceptions are always affected by misperceptions (e), however, it helps to understand why agent-level status trajectories (Figure 1a) and the resulting macro-level status dynamics (Figure 1) do not produce status differentiation when agents interact globally. Previous models could not see this phenomenon, partly because they added instead of averaging dyadic deferential gestures (with the undesirable effects that we document in Appendix B), and partly because they only studied an all-to-all-interaction scenario.

Status Hierarchies in Artificial Heterogeneous Societies. Since widespread heterophily leads to unrealistic macro outcomes, and overwhelming evidence suggests that status-similar interactions are frequent, although not exclusive, we now relax the assumption of agents' homogeneity in their tolerance of status-dissimilar interactions. In particular, following the empirical literature discussed in the section on Model Dynamic, we assume that agents' tolerance for status-dissimilar others varies according to their status. Namely, we simulated the model by assigning low-status agents greater tolerance toward interactions with status-dissimilar agents so that low-status agents accept interactions with both low- and high-status agents, whereas high-status agents tend to interact among themselves. This, we believe, is a realistic scenario, especially in social

settings where high-status actors have the monopoly over important resources and low-status actors may be willing to endure asymmetric relationship in the attempt to secure some of these resources.[13]

The macro-level outcomes of this scenario are presented in Figure 2 for a set of 36 parameter combinations covering the entire parameter space defined by the two agent-level attributes that are still homogenous across agents, that is, agents' propensity to imitate others' deferential gestures (w) and agents' concern for symmetry (s).

Let us start with the simulated status–quality gap (upper panel). Compared to Figure 1, this second scenario in which heterophily is heterogeneously distributed still produces the expected effect for imitation ($w \rightarrow 1$), however, it is better at modeling the counterbalancing effect of the sour grapes heuristic: as agents' concern for symmetry increases ($s \rightarrow 1$), the effect of imitation on the status–quality gap becomes less strong.

Results for the "status–quality re-ordering" measure (central panel) also differ from the homogenous society scenario. We find again that agents' intolerance to unreciprocated deference attributions ($s \rightarrow 1$) increases status reshuffling. In addition, however, the model is now better at producing the effect of the imitation heuristic (more imitation leads indeed to less coherence between quality and status hierarchies).

Finally, the new scenario is consequential for trends in the Gini coefficient (bottom panel). While the counterbalancing effects of the imitation and sour grapes heuristics are confirmed, two new regularities emerge. First, the absolute levels of status concentration are, under the new condition, much higher, with a Gini coefficient around 1, for moderate to high level of social influence (w). This effect persists even when agents' have strong symmetry concern (s) and thus give strong deference penalties. Second, a complex interaction between the two mechanisms emerged. When both the punishment associated to the sour grapes heuristic ($s \rightarrow 1$) and the importance of imitation ($w \rightarrow 1$) increase, we find less, not more, status equality over time—a counterintuitive result that Gould (2002:1159) was able to anticipate in his theorizing, but that he could not generate with his model (the origin of this result is explained in endnote 18). The regression-based sensitivity analysis reported in Table 2 (panel B) confirms that these patterns can be generalized *across the model's entire parameter space*.[14]

In sum, moving from an artificial world in which agents share the same preferences for status-different interactions to one where low-status agents interact with both status-close and status-distant agents, whereas high-status agents tend to interact among themselves, has produced a macroscopic
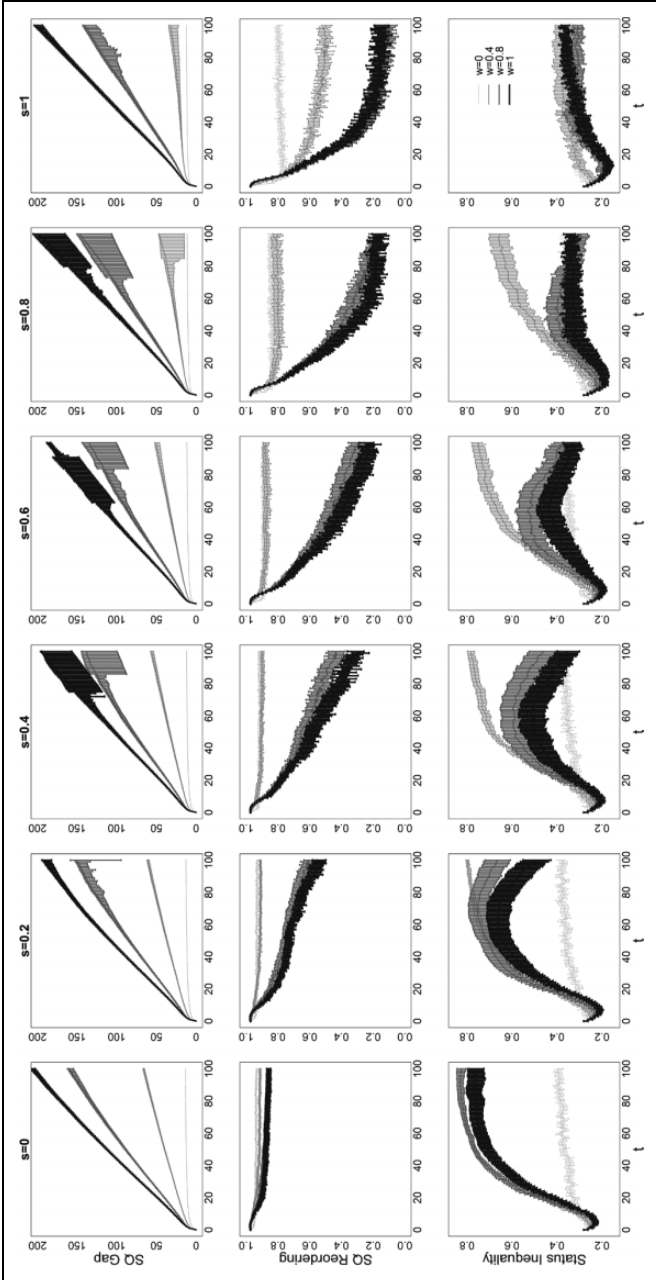
Figure 2. (Experimental condition: status-dependent heterogeneity on agents' propensity h to interact with status-dissimilar partners). Evolution of the simulated values of Status–Quality gap (decibel scale; top panel), Status–Quality re-ordering (ρ; central panel), and status inequality (Gini; bottom panel) over 100 iterations (x-axis) as a function of agents' sensitivity to imitation (w; lines) and symmetry concern (s; columns). Values are averaged across 100 replications for each parameter combination and time period (whiskers for 95 percent confidence intervals). $N = 30$ agents.
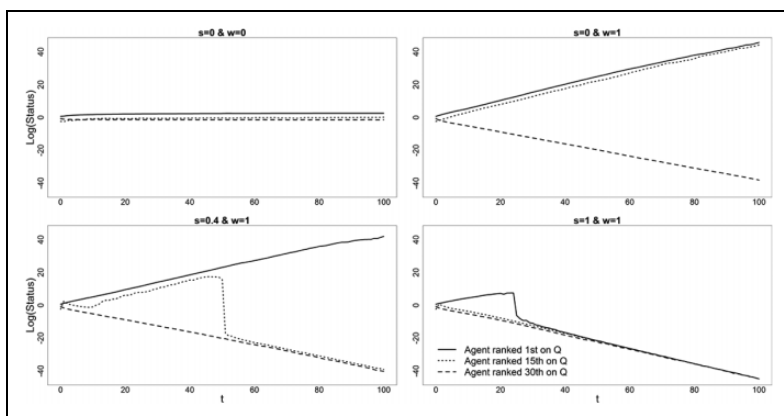
Figure 2a. (Experimental condition: status-dependent heterogeneity on agents' propensity h to interact with status-dissimilar partners). Evolution (over 100 iterations, x-axis) of the status (y-axis) of the agents ranked 1st, 15th, and 30th on the exogenous hierarchy of the intrinsic quality Qi. For each agent, status values are averaged over 100 replications of the model and they are plotted on a logarithmic scale.

behavior of simulated status hierarchies that is improved in the following three respects: (1) the counterbalancing effect commonly associated with the symmetry concern mechanism is now tangible also with respect to the "quality-status gap", (2) the amplifying effect of imitation is now also visible with respect to quality-status re-ordering, and (3) status concentration (Gini coefficient) now reaches fairly high levels, thus indicating that our model, under specific conditions, can also generate status distributions that approximates without, however, ever reaching winner-take all structures. The theoretical logic behind the formulation of the two core, counterbalancing mechanisms is corroborated by the population-level outcomes the model generates.

Status trajectories in artificial heterogeneous societies. The analysis of the micro-level status trajectories (Figure 2a) generated by the model in which agents are heterogeneous in their propensity to interact with status-dissimilar others confirms that both cumulative advantage and its counterbalancing mechanism of symmetry concern generate individual-level effects that are in line with our theoretical expectations.

When neither imitation nor symmetry are at work ($w = 0$ and $s = 0$), status trajectories fluctuate randomly. By contrast, when imitation is maximal ($w = 1$), agents' status trajectories show strong rich-get-richer dynamics,

in which the agents with highest and even moderately high intrinsic quality progressively diverge from those at the bottom of the status hierarchy. This trend is counterbalanced, however, when symmetry concern increases. Even when agents punish deference asymmetries only moderately ($s = 0.4$), the status trajectories of the agents at the top and the bottom of the intrinsic quality hierarchy continue to diverge, whereas agents with "intermediate" initial quality progressively experience status decrements and move closer to the bottom of the status distribution. Finally, when symmetry concern is maximum ($s = 1$), the cumulative advantage component of the model is completely counterbalanced by the sour grapes heuristic: the status trajectory of the top agents, under the pressure of strong deference "penalties" from low-status agents, converges with the trajectory of the agents at the bottom of the quality hierarchy.

To understand this phenomenon, let us consider a low-status agent A0 and a high-status agent A1. Under the assumption of status-dependent asymmetric interactions, A0 is likely to accept to interact with A1, whereas A1 will not interact with A0 except at the model's initialization. In terms of deference gestures, since at the outset A0 is likely to receive an amount of deference from A1 that is lower from what it gave to A1, in subsequent iterations A0 will confer negative deferential gestures to A1, thus decreasing A1 overall status. One may wonder whether this process may be counterbalanced by the deference A1 could receive from its status-similar partners. This is, however, unlikely, since these attachments, coming from status-similar others, are likely to be small in absolute value (see equation 6a and b). In sum, as the concern for symmetry increases, high status individuals will receive an increasing number of negative deference gestures, and their status trajectories may get closer to those of the low-quality agent.[15] In the aggregate, these micro-level dynamics explain the inverse relationship between symmetry and levels of quality-status re-ordering and Gini observed in Figure 2.

Robustness checks

To test the robustness of the population-level patterns generated under the assumption of status-dependent asymmetric interactions, we introduced additional agents' heterogeneity in our artificial society. First, we removed the assumption that agents are homogenous in their concern for symmetry "s" (see the section on Model Dynamic, equation 6a and b). In particular, since in the previous scenario we assumed that low-status actors are willing to interact with high-status actors for instrumental reasons, here we also
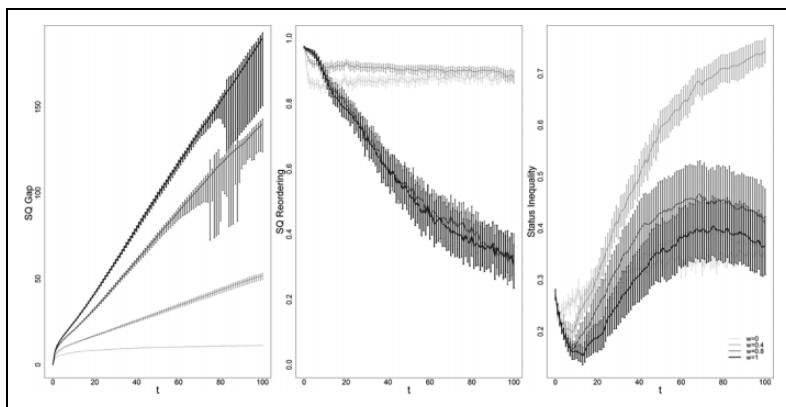
Figure 3. (Experimental condition: status-dependent heterogeneity on agents' propensity *h* to interact with status-dissimilar partners and on agents' sensitivity *s* to symmetry concern). Evolution of the simulated values of Status–Quality gap (decibel scale, top panel), Status–Quality reordering (ρ; central panel), and status inequality (Gini; bottom panel) over 100 iterations (*x*-axis) as a function of agents' sensitivity to other deference attributions (*w*; lines). Values are averaged across 100 replications for each parameter combination at every time period (whiskers for 95 percent confidence intervals). *N* = 30 agents.

consider the possibility that low-status actors are less sensitive to unreciprocated deferential gestures. Since deferential asymmetries are more likely to occur among status-distant agents, low-status actors need to put up with the scorn of unreciprocated deferential gestures if they want to seek high-status relationships. In contrast, since high-status actors tend to interact among themselves, it is plausible to assume that they will develop an hypersensitivity to relatively small differences in the amount of deference exchanged (on the long history of the concept of the "narcissism of minor differences," see Block 1998).[16]

Figure 3 visualizes the model's macroscopic behavior under this additional assumption for six values of agents' propensity to imitate other deferential gestures (*w*), which is the only agent-level attribute that is still assumed to be homogenously distributed across the population. The following four main findings are worth reporting: the stronger the imitation heuristic (*w*→1), (1) the greater, on average, the disconnect between agents' status and their initial quality (left plot); (2) the greater, on average, the lack of coherence between quality and status hierarchies in the aggregate (i.e., "rho" decreases; central plot); (3) the greater the increase in status concentration,
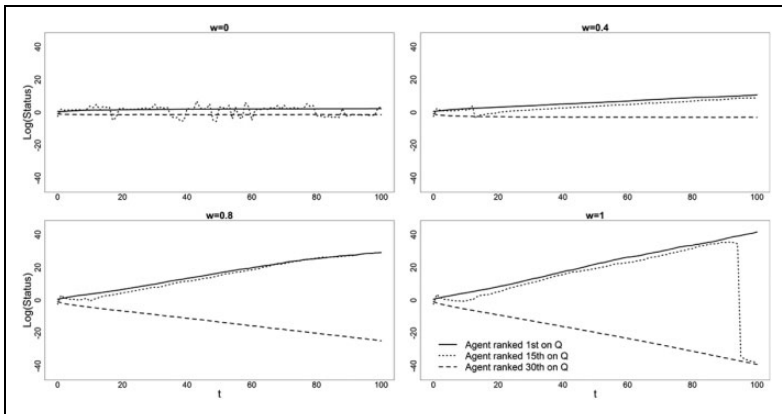
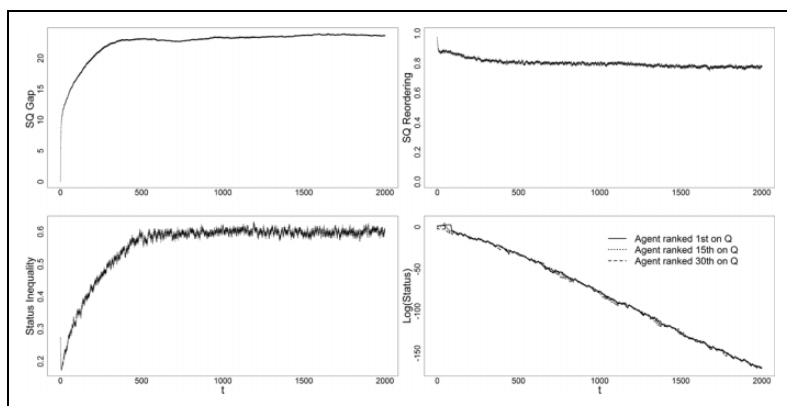**Figure 3a.** (Experimental condition: status-dependent heterogeneity on agents' propensity h to interact with status-dissimilar partners and on agents' sensitivity s to symmetry concern). Evolution (over 100 iterations, x-axis) of the status (y-axis) of the agents ranked 1st, 15th, and 30th on the exogenous hierarchy of the intrinsic quality Qi. For each agent, status values are averaged over 100 replications of the model and they are plotted on a logarithmic scale.

even though this effect is not linear for all levels of social influence (w). Finally, (4) the model's dynamic is still capable to generate fairly high Gini's absolute values, thus suggesting that the imitation heuristic can lead toward winner-take-all-like distribution of status.

At the micro level (Figure 3a), we observe that, differently from previous scenarios in which agents share the same concern for symmetry, the status trajectory of the agents at the top of the initial hierarchy of intrinsic quality diverges from the trajectory of low-status individuals, even under adverse conditions. This occurs because low-status agents are now more tolerant of unreciprocated deferential gestures and therefore do not retaliate with strong deference penalties.

Finally, we also relax the assumption of homogeneity in imitation (see the section on Model Dynamic, equation 5). Empirical network studies (see, among others, Campbell, Marsden, and Hurlbert 1986; Huang and Tausig 1990; Lai, Lin, and Leung 1998) suggest that actors have different access to information according to their status, high-status actors being more and better informed than low-status actors. As a consequence, we assume that high-status agents are less sensitive to social influence than low-status agents.[17]

Figure 4. (Experimental condition: status-dependent heterogeneity on agents' propensity h to interact with status-dissimilar partners, on agents' sensitivity s to symmetry concern and to other deference attributions w). Evolution of the simulated values of Status–Quality gap (decibel scale; top panel), Status–Quality re-ordering (ρ; central panel), and status inequality (Gini; bottom panel) over 2,000 iterations (x-axis). Values are averaged across 100 replications for each parameter combination and time period (whiskers for 95 percent confidence intervals). $N = 30$ agents. *Last Panel*: Status (y-axis) of the agents ranked 1st, 15th, and 30th on the exogenous hierarchy of the intrinsic quality Q_i. For each agent, status values are averaged over 100 replications of the model and they are plotted on a logarithmic scale.

Figure 4 visualizes the model's macroscopic behavior under this additional assumption. This is the most complex scenario, but the simplest in terms of parameter structure, thus we were able to simulate it over a longer temporal window, namely 2,000 iterations. In this way, we were also capable to test the model's robustness over the long run. Under this scenario containing (specific forms) of status-based heterogeneity on all agent-level attributes, we find patterns that, once again, are coherent with our expectations. Indeed, the model still produces (1) a growing gap between agents' initial quality and their final status (left plot), (2) a progressive disconnect between agents' rank within the initial hierarchy of quality and their position within the status hierarchy (central plot), and (3) a sizable growth in the concentration of status, hence in the asymmetry of the underlying distribution, as measured by the Gini coefficient (right plot). Moreover, each of these trends reaches a plateau in the long run, thus suggesting that the imitation heuristic—which is responsible for the process of cumulative advantage—and the sour grapes heuristic—which should

counteract the amplifying effect of the previous mechanism—are properly represented and well balanced within our model.[18]

Overall, considering the set of simulation results presented in this section, we conclude that the introduction of status-based heterogeneity with respect to symmetry concern and imitation does not alter the qualitative structure of the aggregate patterns when compared to the model in which heterogeneity is limited to heterophily.

Discussion and Conclusion

In human (Gould 2002; Henrich and Gil-White 2001; Martin 2009) and animal societies (Chase 1980; Bonabeau, Theraulaz, and Deneubourg 1999) alike, status hierarchies and inequality are omnipresent. In this article, we focused on deference-based status hierarchies, that is hierarchies that appear when actors rely on status cues like income, wealth, education, or other socially constrained, individual-level characteristics to determine the amount of respect, esteem, or prestige that a given actor deserves.

Since deference-based status hierarchies are difficult to measure, we adopted as our empirical benchmark some basic features that are common to virtually all distributions of status resources—the latter being easier to quantify. These recurrent macroscopic features are a large, increasing gap between the underlying actors' quality, talent, or value, and the amount of resources the actor cumulates, and, on the other hand, high, potentially increasing over time, asymmetry, thus distributive inequality. In addition, we noted that some strongly asymmetric distributions, combine strong, stable macro-level asymmetry with constant rank re-ordering at the micro level; a phenomenon, we suggest, that may also characterize deference-based status hierarchies. This article is a direct attempt at modeling dyadic deference gestures to study under which conditions the aggregation of a myriad of local, dyadic deference exchanges driven by counterbalancing micro-level mechanisms, that is, socially influenced quality perceptions and deference penalties for unreciprocated deference attributions, lead to status hierarchies that qualitatively reproduce the three macroscopic patterns summarized above.

Within the large scholarship on status hierarchies, two formal models, i.e., Gould (2002) and LPT (2009), explicitly model dyadic deferential gestures and the sequence of cognitive and relational evaluations driving them and consider two of the abovementioned macroscopic patterns, namely the gap in magnitude and rank between actors' quality and status.

We re-implemented these two models within a common agent-based computational framework and reanalyzed them. Having performed a more extended analysis of the parameter space than the numerical analysis presented by the authors (see Appendix B), we found that (1) the macroscopic outcomes expected from the micro-level mechanisms of social influence and reciprocity actually emerge only within certain regions of the parameter space. This should be considered a problem at least until realistic parameter values remain unknown. (2) Some macroscopic trends are unrealistic, for instance, the unlimited, exponential growth of the status–quality gap. (3) Finally, neither Gould's nor LPT's model generate realistic macro-level patterns with respect to the indicator of status inequality (i.e., Gini coefficient).

These inconsistencies notwithstanding, these previous models contain important theoretical insights. Thus, differently from many replication studies, whose main goal is to show that part of the original results could not be replicated (see, for instance, Galan and Izquierdo 2005; for an overview of different replication strategies, see Hales, Rouchier, and Edmonds 2003; Meadows and Cliff 2012; Van de Rijt, Siegel, and Macy 2009; Wilensky and Rand 2007; Will and Hegselmann 2008), we followed the "tapas" (standing for "Take A Previous model and Add Something") principle —according to which "one takes an existing model and successively explores the assumption space through incremental additions and/or the relaxation of initial assumptions" (see Fagiolo, Moneta, and Windrum 2007:219). Namely, we enhanced previous models with the aim of developing a more general and realistic model of the emergence of deference-based status hierarchies.

We pursued this goal by introducing three major substantive novelties. First, we moved away from the assumption of utility maximizing/optimizing actors and postulated instead that deferential gestures are driven by simple cognitive heuristics, like imitate-the-majority for quality perceptions and sour grapes for dyadic deference attributions. On the basis of the empirical and experimental evidence available, these heuristics are consistent with the way human cognition (i.e., in determining what is cognitively salient) and emotions (i.e., distaste for disrespect) work. Second, we introduced a more general mechanism of partner selection based on status similarity that improves over previous models' assumption that deferential gestures take place within an all-to-all network. Our framework encompasses both scenarios in which patterns of interactions are local and occur mainly among status-similar agents, and scenarios in which dyadic interactions occur among any and all pairs of alters.

Finally, we implemented the model's core parameters as actor-level attributes rather than homogeneous, population-level properties. This allows for the inclusion of various forms of heterogeneity.

The flexibility of the agent-based computational methodology is what made these substantive changes possible. Although this simulation method is still used in economics within a utility-maximizing and/or game-theoretic framework (see, for a treatment of ABM entirely based on this, Shoham and Leyton-Brown 2009), it is not, per se, limited to this approach. The cognitive and emotional heuristics we implemented are, we believe, a good example of the generality and flexibility of the computational method. The latter comes with a cost, however. A common criticism (see for an early statement, Sørensen 1976; see also Gould 2002:1169-70; from the ABM perspective, see Axtell 2000) concerns the absence of close-form analytical solutions, and the consequent uncertainty about the model's behavior for the regions of the parameter space that are not sampled. Especially when empirical data are deficient, sensitivity and robustness analyses constitute the crucial tool to handle this problem (on its importance in the analysis of ABMs, Helbing and Bialetti 2012, 42, 48, 50; see Railsback and Grimm 2011:ch. 23). To make this operation possible, it is necessary to constrain (at least) the model's major parameters to vary on a defined and meaningful interval. This is what we did. Thus, differently from previous models, we could study our model over a range of parameter values that covers its entire parameter space.

On these substantive and methodological bases, we obtained three results of general interest. First, we found that specific interaction patterns strongly affect the functioning of the two core micro mechanisms, namely the capacity of the imitate-the-majority heuristic to trigger a process of cumulative advantage and the capacity of the sour grapes heuristic to counterbalance it. In particular, the more actors value interaction with status-similar others, the more the combination of these two mechanisms produces status hierarchies with features qualitatively similar to those of real-world status cues/indicators (i.e., increasing gap between actors' quality and status and large status asymmetry). Second, we found that a specific form of status-based heterogeneity in actors' propensity to interact with status-dissimilar others is especially consequential for the proper functioning of the model. In particular, when low-status actors interact with both low- and high-status actors, whereas high-status actors mainly keep it to themselves, a considerable amount of status concentration is reached, to the point that the emergent status hierarchies tend toward winner-take-all distributions. It is also under this condition that the model's dynamic is able to generate,

consistently over the entire parameter space, the counterbalancing effect of the sour grapes heuristic. Remarkably, these results are robust and do not show any qualitative change when other forms of status-based heterogeneity are introduced.

Finally, our simulation showed that the mechanisms of social influence and symmetry concern should not be expected to have the same aggregate effect for all dimensions of status distributions. In fact, while, under certain interaction regimes, the imitate-the-majority heuristic is likely to trigger a cumulative advantage process that leads to greater status–quality gap, shuffling in ranks, and status concentration, the sour grapes heuristic counterbalances this effect only with respect to the status–quality gap and the status concentration. In contrast, the sour grapes heuristic produces macroscopic consequences going into the opposite direction with respect to status–quality re-ordering. This fact, a posteriori, is easily understood, since deference penalties essentially act, in our model, as a constant source of noise that provokes rank switching—LPT (2009:780) had a similar intuition when they hypothesized that "symmetry lengthens the time it takes for status position to stabilize." Our analysis of typical agents' status trajectories also suggests, however, that status re-ordering affects agents with intermediate quality much more than those at the top/bottom of the quality hierarchy.

We believe that these results are important for at least three general reasons. First, as recent methodologically sophisticated studies by sociologists (see Van de Rijt 2013; Van de Rijt, Shor, Ward, and Skiena 2013), economists (Bask and Bask 2013), and physicists (see Grabowicz and Eguiluz 2012) have documented, it is difficult to ascertain when a cumulative advantage process is in place using observational data and what are the factors that contain its inequality effect. By producing macro-level statistical regularities on the basis of clearly defined micro-level mechanisms, our work provides a useful benchmark and a flexible computational device that can be widely used to study cumulative advantage and counterbalancing mechanisms in very different empirical settings. Second, as Batty (2006:594, 595) noted in his study of cities' population, stochastic growth models that contain only cumulative advantage mechanisms are not able to generate realistic trends in rank re-ordering. In this respect, our work combines a stochastic growth models (this is the part of the model related to the imitate-the-majority heuristic) with a substantive mechanism, the sour grapes heuristic that is able to generate a varying amount of rank shifts over time. Finally, the strength of our findings is corroborated by the fact that we generated fairly strong asymmetric status distributions (as reflected

by the high Gini coefficients) under "unfavorable" conditions for their emergence (namely uniform distributions and symmetric distributions varying from negative to positive infinite, see Farmer and Geanakoplos 2008:§ 6.4 and 6.9).

In conclusion, we highlight three directions for further research. First, although we have already started to pursue this line of analysis (preliminary results are available upon request), a necessary step to generalize our model to large-scale, real-world social groups is to study the model's behavior for larger populations of agents. Second, a theoretical modification to further increase the realism of the model is to conceive actors' status as a combination of deference gestures received and of the status of those providing deference. This would make it possible to extend the comparison of our model to Bothner et al.'s (2010) study, which shows, although under unrealistic behavioral assumptions, that the status of the deference senders can be consequential for trends in status inequality. Third, at the moment, none of the core parameters of the model are empirically calibrated. Ideally, if we could estimate, for instance, individual sensitivity to others' deferential gestures and to differences in dyadic deference, we may be able to constrain the functioning of the imitate-the-majority and the sour grapes heuristics, thus eliminating all those model outcomes that, although theoretically interesting, do not occur in the real world. Collecting appropriate empirical information on these individual-level attributes is not easy, however. Among the methodological options available, we regard lab and field experiments as especially promising. In particular, as done with respect to quality evaluations of cultural products (see Salganik and Watts 2009), one can develop an experimental design in which actors formulate quality evaluations and deference attribution under different partners' behavior. This would make the empirical calibration of the ABM presented in this article possible.

Appendix A

Pseudo-code

Note: G = Gould model; LPT = Lynn, Podolny, and Tao model; MB = Manzo and Baldassarri model.

Models initialization.

1. *Create N agents* (if G = on or LPT = on, then $N = 30$)
   SET agents' intrinsic Quality (Q_j) $\sim N(0,1)$
   SET agents' sensitivity to reciprocity concern ("s") $\sim U(x, y)$

SET agents' sensitivity to social influence ("w") $\sim U(x, y)$
if MB = on, then SET agents' tolerance to status dissimilarity ("h")
$\sim U(x, y)$

(see Table 1 for a note on s, w, and h)

2. *Create a full-connected network among agents*
Create a links' variable "a" in which to store agent i's deference to j

3. *Determine the first deferential gesture* ($a_{ijt = 0}$)
For each agent i,
    For each agent i's neighbor j,
    if G = on, then SET $a_{ijt = 0}$ = see LPT (2009: equation A4)
    if LPT = on or MB = on, then SET $a_{ijt = 0}$ = equation (2; see
    section on Model Initial State)

4. *Determine the first status hierarchy*
For each agent i,
if G = on or LPT = on, then SET agent i's status $S_{it = 0}$ = see LPT
(2009:table C1, step 5)
if MB = on, then SET agent i's status $S_{it = 0}$ = equation (3; see section
on Model Initial State)

Models Dynamic (only for LPT and MB)
Repeat T times (if LPT = on, then $T = 20$)

5. If MB = on, then *Determine status-dissimilar acceptable "partners"*
For each agent I,
    For each agent i's neighbor j:
        determine if j is an agent with which i wants to interact (see sec-
        tion on Model dynamic, equation 4) execute equations (6) and 7
        only for selected "partners"

6. *Determine agents' perception of other agents' quality* (q_{ijt})
if LPT = on, then SET q_{ijt} = see LPT (2009:table C1, rounds 1–20,
step 2)
if MB = on, then SET q_{ijt} = equation (5; see section Model dynamic)

7. *Determine the agents' deferential gestures* (a_{ijt})
if LPT = on, then SET a_{ijt} = see LPT (2009:table C1, rounds 1–20, step 3)
if MB = on, then SET a_{ijt} = equation (6a), (6b) (see section on Model
dynamic)

8. *Determine the agents' status* (S_{it})
if LPT = on, then SET S_{it} = see LPT (2009:table C1, rounds 1–20, step 4)
if MB = on, then SET S_{it} = equation (7; see section Model dynamic)

Appendix B

Reanalysis of Gould's and LPT's Models

We were attracted to Gould (2002) and Lynn, Podolny, and Tao (2009; LPT, hereafter) because they explicitly model the emergence of status hierarchies and do so in a sophisticated way, by combining two micro-level, counterbalancing mechanisms. However, we felt the need to develop our own model when we realized that both models in fact lead to macro-level consequences that are only partially consistent with the theoretical expectations formulated by the original authors themselves.

This appendix documents our critical stance. We summarize the results of our extensive and systematic numerical re-analysis of Gould and LPT's models based on our implementation of these models into an agent-based computational model (to see how we embedded the core equations of the two models into a computational framework, see the pseudo-code in Appendix A). In particular, we compute the former and simulate the latter for a large set of values of the two main parameters Gould and LPT are interested in, that is, the weight of social influence (w), which determines the extent to which the actor's perception of the quality of a given actor is influenced by the deference attributions this actor received by all other actors, and symmetry concern (s), which affects the extent to which actors sanction unreciprocated deferential gestures.[19]

As previously noted, while the parameter "w" varies between 0 and 1, the parameter "s" is positively unbounded in both Gould's and LPT's model, which makes it impossible to approximate an exhaustive analysis of the model parameter space. Thus, we only could perform an extensive, but systematic, analysis of this space. We explored 385 parameter combinations covering the entire range of w (11 values between 0 and 0.95) and a large subset of s (35 values from 0.1 to 500). In the case of LPT, we also simulated the model under two different levels of actors' quality misperception, thus overall systematically exploring 770 parameter combinations.[20]

The reanalysis of Gould's model. Gould (2002:1157) admitted that the central equation giving the optimal amount of deference that each actor should give each other actor in order to maximize his or her utility, is "cumbersome to interpret." That is why Gould decided to explore the behavior of his model by numerically computing the status hierarchy that it generates. Under the specific parameter set he studied, the graphical illustration provided by Gould (2002:1158) supports his theoretical claim that status inequality is

enhanced by actors following other deferential gestures but reduced when they are more concerned with deference reciprocation. However, when subjected to a more comprehensive numerical analysis, the generality of this conclusion is called into question.

Figure 5 presents results from our agent-based computational implementation of Gould's model. We report three aspects of the simulated status hierarchies, that is, the status–quality gap (top panel), the status–quality re-ordering (middle panel), and the inequality of the status distribution (bottom panel; see the section on The Model's Macroscopic Outcomes). Plots cover the full range of values for social influence w on the x-axis, while, to increase readability, columns only report a selection of values of symmetry concern s—a regression-based analysis of the effect of w and s taking into account all the 385 parameter combinations studied confirms the robustness of the trends visualized in Figure 5 (regression results are available upon request).[21]

Let us start with the macro-level effect of the intensity with which the micro-level cumulative advantage mechanism posited by Gould is supposed to operate (parameter w). According to Gould's own conclusions, we would expect to find that the more actors rely on others' deference attributions, the greater the status–quality gap and the status inequality. Our reanalysis of Gould's model shows a more complex picture. With respect to the status–quality gap (top panel of Figure 5), a very weak positive, monotonic relation is visible only in a very specific region of the parameter space, namely when s is very high ($s = 50$). By contrast, as s decreases, the relationship between social influence and status–quality gap is positive for some values of w, and negative for others (for instance, for $s = 2.5$ and $w < 0.5$, the parameter space studied by Gould, we find qualitatively similar results). Finally, when s is low, an increase in w leads to a monotonic decrease in the status–quality gap, which is contrary to the meaning Gould gave to the social influence and "symmetry" mechanisms. Results are even clearer and also contrary to Gould's expectations with respect to status inequality (bottom panel of Figure 5). Indeed, the impact of w on the simulated Gini is virtually nonexistent for the vast majority of parameter combinations.

Moving to the analysis of Gould's second conclusion according to which his model supports the claim that the more actors value reciprocity in deferential gestures, the smaller the gap between quality and status and overall status inequality, our numerical analysis of the impact of s shows that the model works less clearly than one would expect. When comparing horizontally the plots' y-axes, it appears indeed that an increase in agents' concern for symmetry reduces the status–quality gap, but it has no effect regarding the concentration of status inequality.
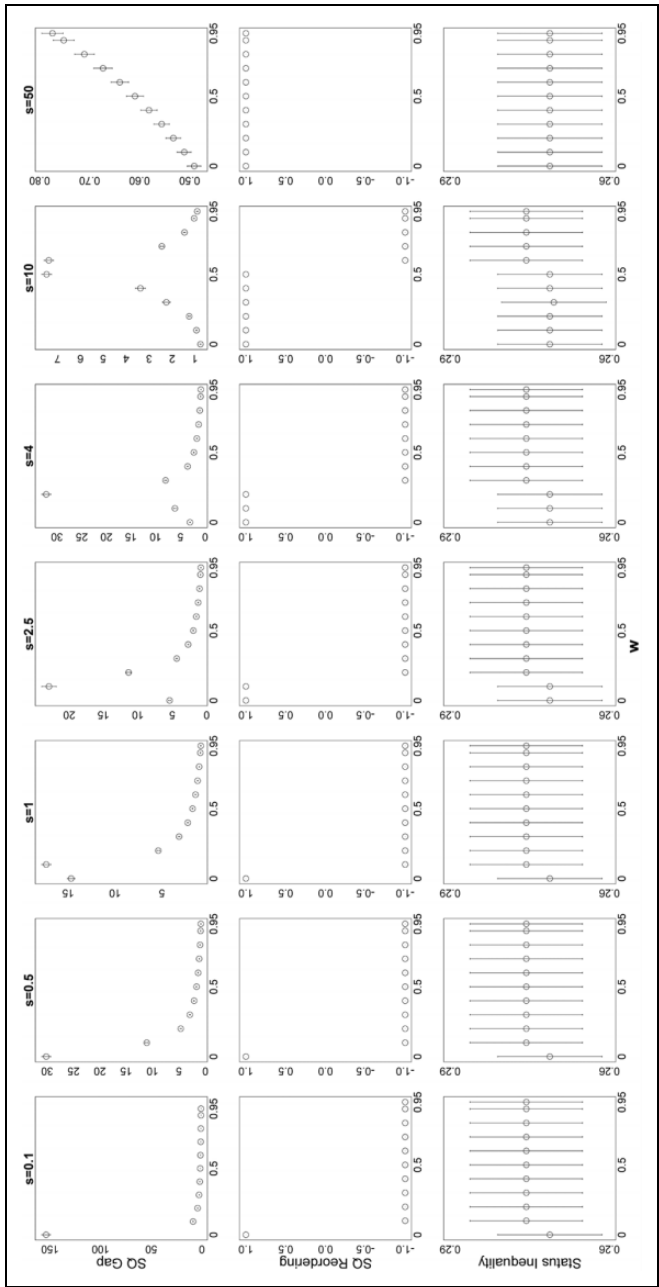
Figure 5. (Reanalysis of Gould's model). Simulated values of Status–Quality gap (decibel scale, top panel), Status–Quality re-ordering (ρ; central panel), and status inequality (Gini; bottom panel) as a function of agents' sensitivity to social influence w (x-axis) and symmetry concern s (columns). Values are averaged across 100 replications of each parameter combination (whiskers for 95 percent confidence intervals). $N = 30$ agents.

Thus, our extensive numerical reanalysis of Gould's model shows that underneath Gould's micro-level equilibrium solution there is a much more complex macro-level story than what so far believed. This does not mean that Gould's (2002:1158) statement according to which his model reveals ''a substantial intensification of status inequality as the importance of social influence relative to exogenous quality increases'' is wrong. It is simply partial. First, it is partial to the measure of status inequality one adopts, namely the effect appears for the status–quality gap but not for Gini. Second, it is partial because, with respect to the status–quality gap, it only appears under very restrictive conditions, namely when agents' symmetry concern is relatively high. However, according to Gould's (2002:1159) own hypothesis, the positive relation between social influence and status inequality should be more visible when ''third-party attributions to alter are not outweighed by the concern for reciprocity,'' that is to say when s is low. A similar argument can be made with respect to the counterbalancing effect of the symmetry concern, namely this effect is robust only when status inequality is measured in terms of status–quality gap, but it is much weaker and uncertain when the concentration of status as measured by Gini is considered.

In our view, this variety of population-level outcomes simply reflects the complexity of Gould's (2002:1157, equation 5) central equation. Indeed, parameters s and w appear both at the numerator and at the denominator, sometimes quadratically, suggesting that the two core mechanisms postulated by Gould have simultaneously a positive and negative, and a linear and nonlinear effect on the definition of the optimal deference attribution. As a consequence, Gould's equilibrium solution contains so many sources of nonlinearity that the model's outcomes are subject to many, qualitatively diverse phase transitions as the model's parameters change. That is why part of our own work consisted in looking for simpler, and more realistic, behavioral rules leading to simpler and more transparent equations.

The reanalysis of LPT model. The quest for simplification and realism already motivated the authors of the second model that we reanalyzed. LPT (2009:795, equation A1) started with the same utility function as Gould but postulated a simpler strategy that actors follow in order to determine their optimal allocation of deference, requiring that actors ''know only their utility functions, and they observe only others' past behaviour.'' Compared to Gould's central equation, this led LPT to a more transparent equation for actors' optimal allocation of deference (ibid:796, equation A8). The meaning of the equation's core parameters is unchanged, however. All other things being equal, the more actors are sensitive to deference attributions

converging on a given actor (parameter ''w''), the more or less (according to values of these attributions) they tend to be deferent to this actor (social influence mechanism), and, on the other hand, the more actors are concerned with unreciprocated deference attributions (parameter ''s''), the lower the amount of deference given to nonreciprocators (''symmetry'' mechanism). Differently from Gould's model, LPT's equation for actors' optimal allocation of deference is not conceived as the equilibrium of the system but as the rule that actors repeatedly adopt to readjust their deference behaviors. LPT simulates this process over 20 time periods for a group of 30 virtual actors.

Figure 6 presents results from our agent-based computational implementation of LPT model. Plots visualize the dynamic evolution over 20 iteration (x-axis) of three aspects of the simulated status hierarchies (y-axis) for a selection of w (gray scaled lines) and s (plot columns) values. Again, a regression-based analysis of the effect of w, s, and e (the amount of errors assumed to affect agents' perceptions of others' quality) taking into account the entire set of 770 parameter combinations we studied confirms the robustness of the trends visualized in Figure 6 (regression results are available upon request).

Let us first consider the status–quality gap (top panel of Figure 6—to allow better visualization, values are expressed on the decibel scale, thus indicating how many times the gap increases/decreases compared to its value at the model's initialization). Clearly, LPT's model is able to generate a growth in the status–quality gap over time and the higher social influence ($w\rightarrow1$), the steeper the increase. By contrast, when agents' symmetry concern (s) increases, the levels of status–quality gap span over a narrower range of values and the inequality-amplifying effect of social influence tends to weaken.

However, the shape of the curves signals a more complex story. Unless s is extremely, (unrealistically) high, the dynamic evolution of the status–quality gap does not reach a steady state. Indeed, the status–quality gap goes through a steep and endless exponential growth and quickly reaches astronomical values, especially when social influence is high. As an example, consider that, even with $s = 4$, which is, according to LPT (2009:665), a high value of symmetry concern, and an intermediate value of social influence ($w = 0.5$), the averaged (over 100 replications) value the gap reaches after 20 iterations is 80,945,590. Thus, contrary to what LPT (2009:776) conclude— ''as expected, the concern for reciprocity acts as a counterbalance to the runaway effect of social influence''—there are reasons to doubt that the counterbalancing works as expected.[22]
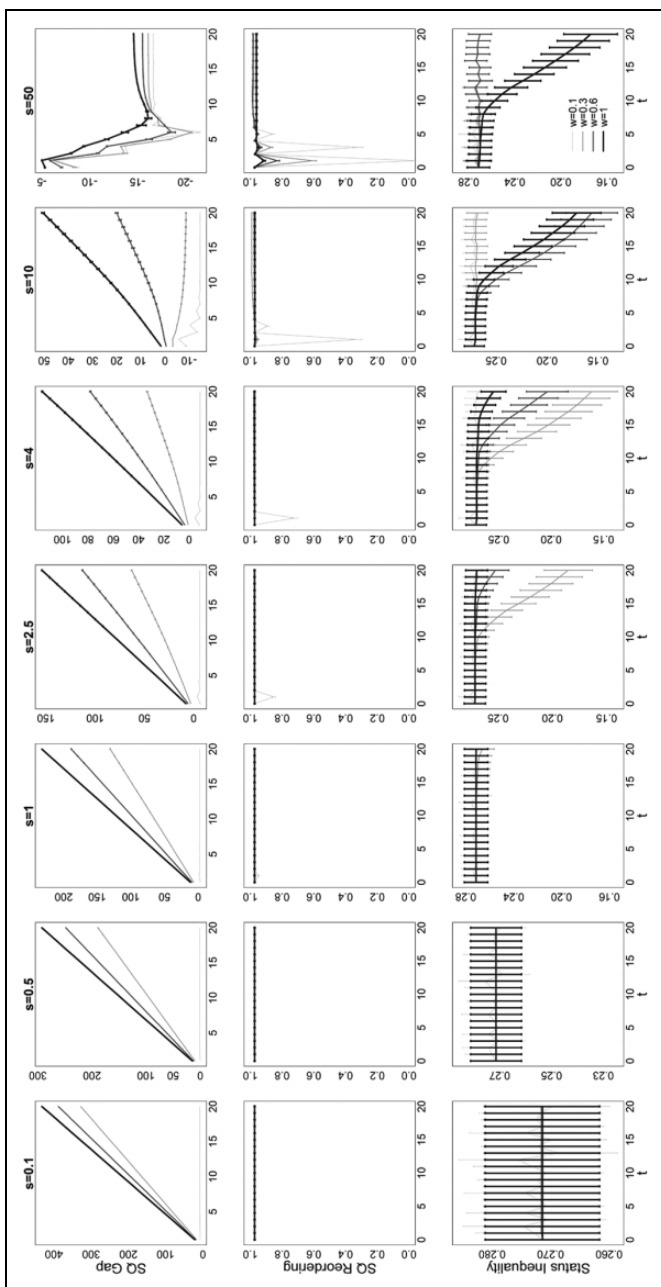
Figure 6. (Reanalysis of Lynn, Podolny, and Tao's model—low level of quality misperception). Evolution of the simulated values of Status–Quality gap (decibel scale, top panel), Status—Quality re-ordering (ρ; central panel), and status inequality (Gini; bottom panel) over 20 iterations (x-axis) as a function of agents' sensitivity to social influence w (gray scaled lines) and symmetry concern s (columns). Values are averaged across 100 replications for each parameter combination at every time period (whiskers for 95 percent confidence intervals). N = 30 agents.

The source of this problem can be explained. As we have seen, LPT follow Gould in conceiving actors' status as the sum of all the deferential gestures that they received. Differently from Gould, who studied the model at equilibrium, however, LPT repeat this aggregative function over multiple iterations. As a consequence, the absolute value of each actor's status is structurally led to increase over time. The social influence (parameter w) operates on this growing quantity and contributes, at each iteration, to increase it even more. In contrast, the reciprocity mechanism works through a single parameter (s) whose values are stable across iterations. Thus, LPT conceptually ask the reciprocity mechanism to do much more than it can numerically do.

Moving to trends in status–quality re-ordering (middle panel of Figure 6), an aspect of status hierarchies that constitutes the major focus of LPT's analysis, our simulated results support LPT's claims only partially. We do not find trace of a sizable effect of symmetry concern (s) nor of social influence (w) on status–quality rank re-ordering. This result is robust against different levels of agents' quality misperception. Indeed, when we replicated LPT's model using the highest level of quality misperception they considered (results not shown but available upon request), in line with LPT's results, the quality and status hierarchies tend to be less concordant than in Figure 6, and neither s nor the amount of social influence w affect this trend.

As already argued in Gould's case, LPT's results are not wrong, they are simply partial. Their conclusion, according to which "relatively small increments of social influence within a group can have a disproportionally large impact on decoupling status from quality among its members" (p. 779) holds true within the small region of the parameter space they studied (namely, $s = 2$ and w going from 0.1 to 1). At least at the latest iteration, we found the same result (on this point, values and plots are available upon request). However, as Figure 6 shows, when the entire range of w and a wide range of s values are considered and their effects are systematically studied over the entire simulation time adopted by LPT, their results are not generalizable.

Finally, let us consider the inequality of the status distributions generated by LPT's model (bottom panel of Figure 6), an aspect that the authors do not consider but that seems an obvious addition for a model on status hierarchies. It is clear that the micro-level cumulative advantage mechanisms associated with social influence (parameter w) is not able to trigger a growth in status inequality. The equalizing effect attributed in theory to reciprocity in deferential gestures (parameter s) is also absent from the vast majority of the model's parameter space.

Taken together, these results lead to the conclusion that LPT's model represents the two micro-level mechanisms of social influence and reciprocity in deferential gestures in such a way that the macro-level consequences of these two mechanisms are not in line with the theoretical rationale behind their introduction. In theory, social influence should explain why status hierarchies emerge and exhibit increasing levels of status–quality disconnection and inequality over time, whereas reciprocity should counterbalance this growth. However, our extensive reanalysis of LPT's model has shown that these macro-level effects are not stable features of the model. Regarding social influence, while it works as expected with respect to status dispersion, it does not have the expected effect on rank re-ordering or status inequality. Considering the latter, no matter what dimension of status hierarchies we look at, agents' reciprocity concerns are not really able to counterbalance the effect of social influence and thus temperate the amount of status inequality.[23]

Acknowledgments

Declaration of Conflicting Interests

Funding

Notes

1. In his analysis of the evolution of cities' size across the world over several centuries, Batty (2006) discovered that, although the overall distribution of cities' population constantly resembles a strongly asymmetric rank/size distribution, the rank of single cities is characterized by large volatility at the micro level.

2. Continuing to rely on this image of actors seems untenable, given the empirical evidence and the theoretical arguments now available, suggesting that it is unrealistic to conceive social actors as optimizing "devices" (in sociology, see Boudon 2003; in economics, Camerer and Loewenstein 2004; Gigerenzer 2008; Goldstein 2009; Hedström 2005; Macy and Flache 1995; Macy 1997; in political science, Ostrom 1998; Sen 2009; in psychology, see Shafir and LeBoeuf 2002; Smith 2008).

3. Although Bothner et al. (2010) propose a different mechanism to contain the growth in status inequality, their formal model of status hierarchy also relies on these three unrealistic assumptions.

4. As this script shows, in order to facilitate the comparison among our own model and Gould's and LPT's models, we implemented the three models within a common meta-agent-based computational model. Every single model as well as the meta-model have been coded in NetLogo 5.0 (see Lytinen and Railsback 2012; Railsback and Grimm 2011; Tisue and Wilensky 2004; Wilensky 1999).

5. Studying dyadic, face-to-face interactions among scientific conference attendees, Barrat et al. (2010) show that encounters—namely time spent discussing together—follow a clear academic-status-based pattern.

6. Our partner selection mechanism resembles a common modeling strategy used by sociophysicians studying opinion dynamics in which agents interact and have a chance to influence each other only if the difference between their opinions is within a given range (see Castellano, Fortunato, and Loreto 2009:608-11).

7. The way we represent agents' quality perception has the form of typical multiplicative stochastic processes studied by physicists interested in generating asymmetric distributions and power laws in particular (see Farmer and Geanaklopos 2008: equation [16]). Namely, the second term of equation (5) resembles a proportionate growth model *à la* Yule or Gibrat (richer units will get larger proportion of resources) or a preferential attachment mechanism (more connected nodes are more likely to get new connections; see, respectively, Andriani and McKelvey, 2006: 1058, 1059, 1961; Farmer and Geanaklopos 2008:§ 6.6; Newman 2005:340-42).

8. A reviewer questioned the consistency of the temporal component in equation (7) noticing that, when a_{jit} is positive, a_{jit} decreases as the ratio t^*/t decreases (i.e., deferential gestures become more remote in time), thus decreasing the final status

S_{it}. By contrast, when a_{jit} is negative, a_{jit} increases as the ratio $t*/t$ decreases, thus increasing the final status S_{it}. In our opinion, this is consistent with the "memory effect" we want to represent, that is, that the more remote the deferential gestures, the weaker their effect on the final's agent status. Let us consider a simple example. An agent *j* receives at iteration 1 two a_{jit} of value -1.5 and 3. Following equation (7), the status of this agent computed at the end of iteration 1 is $[-1.5 \times (1/1) + 3 \times (1/1)]/2 = 0.75$. Let us now imagine that, at iteration 2, the same agent receives only a a_{jit} equal to 3 from the same alter and does not interact with anybody else. In this case, his final status is $[-1.5 \times (1/2) + 3 \times (2/2)]/2 = 1.125$. This difference between iterations 1 and 2 is consistent with what we intend to represent: at time 2, the negative deferential gesture is more distant in time than at time 1, thus its demeaning effect on the agent's status is weaker.

9. LPT (2009:766) seem aware of this difficulty when, with respect to the concept of "status re-ordering" they note that "whether or not reciprocity enables the decoupling of status from quality, however, is unclear."

10. There are nowadays as many ways to compute the Gini coefficient as there are interpretations of it (Yitzhaki and Schechtman 2013). We calculate the coefficient by adapting a procedure, initially implemented by Wilensky (1998), that iteratively computes the area below the Lorenz Curve for the cumulative distribution of status. Our results were numerically consistent with those produced by the function "Gini" implemented in the R package "Ineq." When the distribution of agents' status contained negative values, we rescaled the distribution to a positive range (with minimum equal to 0) before computing the Gini coefficient.

11. In fact, we analyzed a total of 2,420 parameter combinations to explore LPT's (2009: 776-78) finding according to which larger misperceptions of agents' intrinsic quality (parameter *e*) are consequential for status re-ordering. We systematically simulate our model under "low-" and "high-"quality misperception—low and high, respectively, meaning that the variability in the (normal) error distribution is equal to the variability of the (normal) quality distribution (namely $SD = 1$ for both distributions), or, alternatively, that the variability of the former is five times higher than of the latter (namely $SD = 5$ vs. $SD = 1$; see ibid:table 2, panel A1, p. 777). Because of space limitation, we comment only on the "low" error condition (the differences across the two conditions concern the measures' absolute values, not the qualitative form of their trends).

12. A reviewer objected that these results may be "largely driven" by the "artificial scaling choice" we adopted in equation (5), defining agents' perception of others' quality. While we weight the endogenous status component by *w* differently from previous models (see Gould 2002:1156 and LPT 2009:770), we do not weight the exogenous intrinsic quality term by "$1 - w$." According to the

reviewer, this unbalance is at the basis of the observed positive effect of w on the status–quality gap. This is not the case, however: the presence/absence of the positive effect of w on the status–quality gap is robust to different specifications of agents' quality perception. First of all, in a previous version of the model, agents' quality perception was modeled following Gould's and LPT's model, and we obtained a similar aggregate effect of w (results are available upon request). Second, we rerun simulations of the current model reintroducing the weighting $1 - w$ in the first term of equation (5) and results (both plots and ordinary least squares (OLS) regressions, which are available upon request) are remarkably stable. For instance, the estimated positive effect of w on the status–quality gap over the entire parameter space remains substantially unaltered (149.4 vs 155.4). Moreover, the model containing the $(1 - w)$ weighting factor produces incoherent results in the extreme scenario in which each agent interacts with everyone else ($h = 1$). Finally, despite its mathematical elegance, there is no empirical reason to weight both terms of equation (5) by $1 - w$ and w. The latter, in fact, implies the existence of a trade-off between considering alter's intrinsic quality and relying on others' deferential gestures.

13. To implement this scenario, we changed the way agents are assigned h values at the beginning of every iteration. In particular, for low-status agents we drew h from a uniform distribution defined over the interval [0.8, 1], whereas we used the interval [0.1, 0.2] for high-status agents. A low-/high-status agent is defined as an agent that, at the beginning of a given iteration t, falls below/above the median of the status distribution. Note that the introduction of heterogeneity on h can lead to situations in which *ego* is willing to interact with *alter*, while *alter* is not (see section Model Dynamic, equation 4). As we will explain later (see section Status Trajectories in Artificial Heterogeneous Societies), this is important to understand the micro-level origin of the population-level trends generated by the model.

14. As discussed in endnote 12, we also rerun this set of simulations reintroducing the weighting $1 - w$ in the first term of equation (5). Again, results (available upon request) are remarkably stable. In particular, the estimated positive effect of w on the status–quality gap over the entire parameter space remains substantially unaltered (186.65 vs. 180.45).

15. For instance, consider that the proportion of negative deference gestures received by a typical agent ranked first on the quality hierarchy: this proportion is lower than 1% when $s = 0.4$, whereas it reaches 50% at the 45th, 20th, and 8th iterations (and 100% at the 71th, 40th, and 24th iterations) when $s = 0.6, 0.8$, or 1, respectively.

16. Operationally, we changed the way agents are assigned s values at the beginning of every iteration. In particular, we drew the values for s from a uniform

distribution defined over the interval [0.8, 1] for high-status agents, whereas we used the interval [0, 0.2] for low-status agents (as defined in endnote 13).

17. Like for h and s (see, respectively, endnotes 13 and 16), we changed the way agents are assigned w values at the beginning of each iteration. In particular, we drew the values for w from a uniform distribution defined over the interval [0.8, 1] for low-status agents, whereas we used the interval [0, 0.2] for high-status agents.

18. The underlying agent-level status trajectories plotted in the last panel of Figure 4 shows that agents' status trajectories first diverge (during about the 100 first iterations), and, then, start to converge, with high-status agents progressively losing their capacity to secure greater amount of status. This is similar to what we observed under the scenario in which agents are only heterogeneous in terms of heterophily (see Figure 2a). There is however an important difference in our model that provides additional insights into how individual status trajectories aggregate into complex large-scale status hierarchies. In the s- and w-homogeneity case, it was s that, when increasing, made the negative attachments addressed by low-status to high-status agents higher in absolute values, thus increasing their weight in the set of attachments received by high-status agents. In the present scenario, it is w instead that produces a similar effect. As w is assumed to be higher for lower-status agents, the deference penalties that they direct to high-status agents will weigh more, amplify, and spread at each iteration through the mechanism of quality perception (see equation 5). Indirectly this helps to understand the micro-level origin of the nonlinear effect of w on status concentration that we observed in the aggregate (see Figures 2 and 3). That, when status-dependent asymmetric interactions are present, stronger imitation tend to lead to lower-status inequality, not more, contrary to theoretical expectations concerning the functioning of cumulative advantage mechanisms, comes from the fact that larger w helps the diffusion of negative deferential attachments low-status agents address to high-status agents, thus, in the end, making the status of high-status agents get closer to that of low-quality agents.

19. One referee raised the issue of the extent to which this analysis can be truly regarded as a reanalysis of Gould and LPT because, he argues, translating a mathematical model into an agent-based computational model requires the introduction of elements that are unspecified and/or unnecessary in a mathematical model. While this is true, for instance, Gould left unspecified the distribution followed by actors' intrinsic quality and LPT did not need to define an order of invocation for their simulated actors, the details required by our agent-based model (ABM) implementation of the two models are not consequential. The proof of this is the capacity of our ABM version of Gould

and LPT to reproduce the results that they obtained within the area of the parameter space that they studied.

20. This contrasts with the limited area of the model's parameter space analyzed by Gould and LPT and with the unsystematic character of their analysis. In particular, Gould (2002:figure 1) only considers $s = 2.5$ and $w = 0.1, 0.2, 0.3, 0.4,$ and 0.5. LPT (2009:tables 1, 2, and 3) consider $s = 1$ and $s = 4$, and $w = 0.20$ and $w = 0.80$. In some simulations, they also consider $s = 2$, or $s = 1$ and $s = 6$, or $s = 1, 2,$ and 6, and $w = 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9$ (see, respectively, LPT 2009:figures 10 and 11, figures 9, and figure 8).

21. As LPT (2000:794; endnote 20) have demonstrated, the Gould (2002:1157, equation 5) original equilibrium solution contains errors. Our numerical analysis is thus based on Gould's equation corrected by LPT (2002:794, equation A4). Also, although Gould assumes that w ranges between 0 and 1 (extremes included), the corrected version of Gould's equation cannot be computed for $w = 1$, which explains why we did not consider this value.

22. LPT seem not to be aware of this phenomenon, probably because they explored only three parameter combinations of s and w, namely $s = 1$ and $w = 0.20$, $s = 4$ and $w = 0.20$, and $s = 1$ and $w = 0.80$, and, above all, because they studied this aspect of the model only looking at the outcome after the first iteration (we thank the authors for sharing this information with us). In passing, note that, at the first iteration, for the abovementioned parameter combinations, our results perfectly match the results shown in table 1 of LPT's article.

23. One objection that may be raised against this conclusion is that we extensively reanalyzed only the form of LPT model containing social influence, "symmetry constraint," and "dyadic-level quality misperceptions." It may be that, one may argue, the variants of LPT (2009:771-72) model containing a collective variant of actors' quality misperception, initial random attachments, diffuse status characteristics, and self-fulfilling prophecy work better than the basic variant. Our reticence to invest time and energy in extensively replicating these variants of the model is that LPT's (2009:780-787) results show that these modifications only accentuate the patterns generated by the basic version, essentially because they all have the consequence of limiting the potentially equilibrant effect of noise during the model's dynamic (see LPT's discussion). This said, we are open to revise our conclusion if an *extensive* and *systematic* reanalysis of these variants of the model should prove that inconsistencies are eliminated when these alternative mechanisms are considered (in passing, note that the "collective" variant of quality misperception is already implemented in our NetLogo implementation of LPT model). Even in this case, however, it would remain the issue of the realism of the micro-level assumptions on which the LPT model is based, realism that, we believe, is now challenged by our own model.

References

Alper, N. O. and G. H. Wassall. 2006. ''Artists' Careers and Their Labors Markets.'' Pp. 813-64 in *Handbook of Economics of Art and Culture*, edited by V. A. Ginsburgh and D. Throsby. Amsterdam, the Netherlands: Elsevier.

Anderson, Cameron, Robb Willer, Gavin Kilduff, and Courtney Brown. 2012. ''The Origins of Deference: When do People Prefer Lower Status?'' *Journal of Personality and Social Psychology* 102:1077-88.

Andriani, P. and B. McKelvey. 2009. ''From Gaussian to Paretian Thinking: Causes and Implications of Power Laws in Organizations.'' *Organization Science* 20: 1053-71.

Atkinson, A. B., T. Piketty, and E. Saez. 2011. ''Top Incomes in the Long Run of History.'' *Journal of Economic Literature* 49:3-71.

Axtell, Robert. 2000. ''Why Agents? On the Varied Motivations for Agent Computing in the Social Sciences.'' Working Paper No. 17, Center on Social and Economic Dynamics, The Brookings Institution, Washington, DC.

Axtell, Robert, Joshua Epstein, and H. Peyton Young. 2001. ''The Emergence of Classes in a Multi-agent Bargaining Model.'' Pp. 191-212 in *Social Dynamics*, edited by Steven N. Durlauf and H. Peyton Young. Washington, DC: Brookings Institution.

Baldassarri, Delia. 2012. *The Simple Art of Voting*. New York: Oxford University Press.

Ball, B. and M. E. J. Newman. 2013. ''Friendship Networks and Social Status.'' *Network Science* 1:16-30.

Banerjee, A. and V. M. Yakovenko. 2010. ''Universal Patterns of Inequality,'' *New Journal of Physics* 12:075032.

Barabási, A.-L. 2009. ''Scale-free Networks: A Decade and Beyond.'' *Science* 325: 412-13.

Barabási, A.-L. and E. Bonabeau. 2003. ''Scale-free Networks.'' *Scientific American* 288:62-69.

Barrat, A., C. Cattuto, M. Szomszor, W. Van den Broeck, and H. Alani. 2010. ''Social Dynamics in Conferences: Analyses of Data from the Live Social Semantics Application.'' The 9th International Semantic Web Conference, Shanghai, China.

Barrera, D. and V. Buskens. 2007. ''Imitation and Learning under Uncertainty: A Vignette Experiment.'' *International Sociology* 22:366-95.

Barrera, D. and V. Buskens. 2009. ''Third-party Effects in an Embedded Investment Game.'' Pp. 37-72 in *Trust and Reputation*, edited by V. Buskens, C. Cheshire, K. S. Cook, and C. Snijders. New York: Russell Sage Foundation.

Bask, M. and M. Bask. 2013. ''Cumulative (Dis)advantage and the Matthew Mechanism.'' Uppsala University and University of Bergen.

Batty, M. 2006. "Rank Clocks." *Nature* 444:592-96. doi:10.1038/nature05302.

Berger, J., B. Cohen, and M. Zelditch. 1972. "Status Characteristics and Social Interaction." *American Sociological Review* 37:241-55.

Berger, J. and H. Fisek. 2006. "Diffuse Status Characteristics and the Spread of Status Value: A Formal Theory." *American Journal of Sociology* 111:4, 1038-79.

Bikhchandani, Sushil, David Hirshleifer, Ivo Welch. 1992. "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades" *Journal of political Economy* 5:992-1026.

Block, A. 1998. "The Narcissism of Minor Differences." *European Journal of Social Theory* 1:33-56.

Blossfeld, Hans-Peter. 2009. "Educational Assortative Marriage in Comparative Perspective." *Annual Review of Sociology* 35:513-30.

Bonabeau, Eric, Guy Theraulaz, and Jean-Louis Deneubourg. 1999. "Dominance Orders in Animal Societies: The Self-organization Hypothesis Revisited." *Bulletin of Mathematical Biology* 61:727-57.

Bothner, M. S., R. Haynes, W. Lee, and E. B. Smith. 2010. "When Do Matthew Effects Occur?" *Journal of Mathematical Sociology* 34:80-114.

Boudon, Raymond. 2003. "Beyond Rational Choice Theory." *Annual Review of Sociology* 29:1-21.

Buskens, V. and W. Raub. 2002. "Embedded Trust: Control and Learning." *Advances in Group Processes* 19:167-202.

Camerer, Colin and F. G. Loewenstein. 2004. "Behavioral Economics: Past, Present, Future." Pp. 3-51 in *Advances in Behavioral Economics*, edited by Colin F. Camerer, George Loewenstein, and Matthew Rabin. Princeton, NJ: Princeton University Press.

Campbell, K. E., P. V. Marsden, and J. S. Hurlbert. 1986. "Social Resources and Socioeconomic Status." *Social Networks* 8:97-117.

Castellano, C., S. Fortunato, and V. Loreto. 2009. "Statistical Physics of Social Dynamics." *Reviews of Modern Physics* 81:591-646.

Chakrabarti, B. K., A. Chakraborti, S. R. Chakravarty, and A. Chatterjee. 2013. *Econophysics of Income & Wealth Distributions*. Cambridge, UK: Cambridge University Press.

Chan, T. W., ed. 2010. *Social Staus and Cultural Consumption*. Cambridge, UK: Cambridge University Press.

Chan, Tak Wing and John H. Goldthorpe. 2007. "Class and Status: The Conceptual Distinction and its Empirical Relevance." *American Sociological Review* 72:512-32.

Chase, Ivan. 1980. "Social Process and Hierarchy Formation in Small Groups: A Comparative Perspective." *American Sociological Review* 45:905-24.

Chase, Ivan and W. Brent Lindquist. 2009. "Dominance Hierarchies." Pp. 566-591 in *The Oxford Handbook of Analytical Sociology*, edited by Hedström Peter and Bearman Peter. Oxford, UK: Oxford University Press.

Cialdini, R. B. 1984. *Influence: The Psychology of Persuasion*. New York: Quill.

Cialdini, R. B. and M. R. Trost. 1998. "Social Influence: Social Norms, Conformity, and Compliance." Pp. 151-192. In *The Handbook of Social Psychology*, ch. 21, edited by D. T. Gilbert, S. T. Fiske, and G. Lindzey. New York: McGraw-Hill.

Clauset, A., C. Shalizi, and M. Newman. 2009. "Power-law Distributions in Empirical Data." *SIAM Review* 51:661-703.

Denrell, J. and C. Liu. 2012. "Top Performers are not the Most Impressive when Extreme Performance Indicates Unreliability." *PNAS* 109:9331-36.

DiPrete, Thomas, A. and Gregory Eirich. 2006. "Cumulative Advantage as a Mechanism for Inequality: A Review of Theoretical and Empirical Developments." *Annual Review of Sociology* 32:271-97.

DiPrete, Thomas, Gregory Eirich, and Matthew Pittinsky. 2010. "Compensation Benchmarking, Leapfrogs, and the Surge in Executive Pay." *American Journal of Sociology* 115:1671-712.

Dragulescu, A. and V. M. Yakovenko. 2001a. "Evidence for the Exponential Distribution of Income in the USA." *Eur. Phys. J. B* 20:585.

Dragulescu, A. and V. M. Yakovenko. 2001b. "Exponential and Power-law Probability Distributions of Wealth and Income in the United Kingdom and the United States." *Physica A* 299:213-21.

Elster, Jon. 2007. *Explaining Social Behaviour: More Nuts and Bolts for the Social Sciences*. New York: Cambridge University Press.

Elster, Jon. 2009. "Excessive Ambition." *Capitalism and Society*, 4:2, article 1.

Eom, Y.-H. and S. Fortunato. 2011. "Characterizing and Modeling Citation Dynamics." *PLoS ONE* 6:e24926. doi:10.1371/journal.pone.0024926.

Epstein, Jon. 2006. *Generative Social Science: Studies in Agent-based Computational Modeling*. Princeton, NJ: Princeton University Press.

Fagiolo, Giorgio, Alessio Moneta, and Paul Windrum. 2007. "A Critical Guide to Empirical Validation of Agent-based Models in Economics: Methodologies, Procedures, and Open Problems." *Computational Economics* 30: 195-226.

Fararo, Thomas J. and Carter T. Butts. 1999. "Advance in Generative Structuralism: Structured Agency and Multilevel Dynamics." *Journal of Mathematical Sociology* 24:1-65.

Farmer, J. D. and J. Geanakoplos. 2008. "Power Laws in Economics and Elsewhere." Working Papers, Santa Fe Institute, Mexico.

Fiske, Susan. 2010a. "Interpersonal Stratification: Status, Power, and Subordination." In *Handbook of Social Psychology*. 3:III:26. http://onlinelibrary.wiley.com/doi/10.1002/9780470561119.socpsy002026/abstract. Accessed on July 24, 2014.

Fiske, Susan. 2010b. "Envy Up, Scorn Down: How Comparison Divides Us." *American Psychologist* 65:698-706.

Fiske, Susan. 2011. *Envy Up, Scorn Down. How Status Divides Us*. New York: Russell Sage Foundation.

Frank, Robert and Philip J. Cook. 1995. *The Winner-take-all Society*. New York: The Free Press.

Galan, José M. and Luis R. Izquierdo. 2005. "Appearances Can Be Deceiving: Lessons Learned Re-implementing Axelrod's 'Evolutionary Approach to Norms." 8:2. http://jasss.soc.surrey.ac.uk/8/3/2.html. Accessed on July 24, 2014.

Gigerenzer, G. and H. Brighton. 2011. "Homo Heuristicus: Why Biased Minds Make Better Inferences." Pp. 2-27 In *Heuristics: The Foundations of Adaptive Behavior*, edited by G. Gigerenzer, R. Hertwig, and T. Pachurt. Oxford, UK: Oxford University Press.

Gigerenzer, G. and W. Gaissmaier. 2011. "Heuristic Decision Making." *Annual Review of Psychology* 62:451-82.

Gigerenzer, Gerd. 2008. *Rationality for Mortals. How People Cope with Uncertainty*. Oxford, UK: Oxford University Press.

Giorgi, G. Maria and S. Nadarajah. 2010. "Bonferroni and Gini Indices for Various Parametric Families of Distributions." *METRON - International Journal of Statistics* 68:1.

Goldstein, Daniel. 2009. "Heuristics." Pp. 140-67. In *The Oxford Handbook of Analytical Sociology*, edited by Hedström Peter and Bearman Peter. UK: Oxford University Press.

Gould, Roger. 2002. "The Origins of Status Hierarchies: A Formal Theory and Empirical Test." *American Journal of Sociology* 107:1143-78.

Grabowicz, P. A. and V. M. Eguiluz. 2012. "Heterogeneity Shapes Groups Growth in Social Online Communities." *Europhysics Letters* 97:28002.

Hales, D., J. Rouchier, and B. Edmonds. 2003. "Model-to-model Analysis." *Journal of Artificial Societies and Social Simulation* 6:4. http://jasss.soc.surrey.ac.uk/6/4/5.html.

Hedström, Peter. 1998. "Rational Imitation." Pp. 306-27 in *Social Mechanisms. An Analytical Approach to Social Theory*, edited by Hedstrom Peter and Richard Swedberg. Cambridge, UK: Cambridge University Press.

Hedström, Peter. 2005. *Dissecting the Social: On the Principles of Analytical Sociology*. Cambridge, UK: Cambridge University Press.

Helbing, D. and S. Bialetti. 2012. "Agent-based Modeling." Pp. 25-70. In *Social Self-organization: Agent-based Simulations and Experiments to Study Emergent Social Behavior*, ch. 2, edited by D. Helbing. Berlin, Germany: Springer.

Henrich, Joseph and Francisco J. Gil-White. 2001. "The Evolution of Prestige. Freely Conferred Deference as a Mechanism for Enhancing the Benefit of Cultural Transmission." *Evolution and Human Behaviour* 22:165-96.

Hertwig, R. and S. M. Herzog. 2009. "Fast and Frugal Heuristics: Tools of Social Rationality." *Social Cognition* 27:661-98.

Huang, G. and M. Tausig. 1990. "Network Range in Personal Networks." *Social Networks* 12:261-68.

Lai, G., N. Lin, and S.-Y. Leung. 1998. "Network Resources, Contact Resources, and Status Attainment." *Social Networks* 20:159-78.

Laumann, E. O. 1965. "Subjective Social Distance and Urban Occupational Stratification." *American Journal of Sociology* 71:26-36.

Leombruni, Roberto and Matteo Richiardi. 2005. "Why are Economists Skeptical about Agent-based Simulations?" *Physica A* 355:103-9.

Lynn, Freda, Joel Podolny, and Lin Tao. 2009. "A Sociological (De)Construction of the Relationship between Status and Quality." *American Journal of Sociology* 115:755-804.

Lytinen, S. L. and S. F. Railsback. 2012. "The Evolution of Agent-based Simulation Platforms: A Review of NetLogo 5.0 and ReLogo." http://condor.depaul.edu/slytinen/abm/Lytinen-Railsback-EMCSR_2012-02-17.pdf. Accessed on July 7, 2014.

Macy, Michael W. and Andreas Flache. 1995. "Beyond Rationality in Models of Choice." *Annual Review of Sociology* 21:73-91.

Macy, Michael W. and Andreas Flache. 2009. "Social Dynamics from the Bottom up: Agent-based Models of Social Interaction." In *The Oxford Handbook of Analytical Sociology*, edited by Hedström Peter and Peter Bearman. Oxford, UK: Oxford University Press.

Macy, Michael W. 1997. "Identity, Interest and Emergent Rationality. An Evolutionary Synthesis." *Rationality and Society* 9:427-48.

Manzo, Gianluca. 2013. "Is Rational Choice Theory *Still* a Rational Choice of Theory?" *Social Science Information* 52:361-82.

Martin, John L. 2009. "Formation and Stabilization of Vertical Hierarchies among Adolescents: Towards a Quantitative Ethology of Dominance among Humans." *Social Psychology Quarterly* 72:241-64.

McKenzie, Alexander J. 2007. *The Structural Evolution of Morality*. Cambridge, UK: Cambridge University Press.

McPherson, J., L. Smith-Lovin, and J. Cook. 2001. "Birds of a Feather: Homophily in Social Networks." *Annual Review of Sociology* 27:415-44.

Meadows, Michael and Dave Cliff. 2012. "Reexamining the Relative Agreement Model of Opinion Dynamics." *Journal of Artificial Societies and Social Simulation* 15:4. http://jasss.soc.surrey.ac.uk/15/4/4.html.

Menger, Pierre M. 1999. "Artistic Labor Markets and Careers." *Annual Review of Sociology* 25:541-74.

Merton, Robert K. 1968. "The Matthew Effect in Science. The Reward and Communication Systems of Science Are Considered." *Science* 159:56-63.

Merton, Robert K. 1988. "The Matthew Effect in Science, II: Cumulative Advantage and the Symbolism of Intellectual Property." *ISIS* 79:606-23.

Miller, John H. and Scott E. Page. 2004. "The Standing Ovation Problem." *Complexity* 9:8-16.

Mitzenmacher, M. 2004. "A Brief History of Generative Models for Power Law and Lognormal Distributions." *Internet Mathematics* 1:226-51.

Muldoon, R. 2007. "Robust Simulations." *Philosophy of Science* 74:873-83.

Newman, Mark E. J. 2005. "Power Laws, Pareto Distributions and Zipf's Law." [Review]. *Contemporary Physics* 46:323-51.

Ostrom, Elinor. 1998. "A Behavioral Approach to the Rational Choice Theory of Collective Action." *The American Political Science Review* 92:1-22.

Pareto, Vilfredo. 1896. *Cours d'Economie Politique*. Geneva, Switzerland:Droz.

Podolny, Joel. 2005. *Status Signals: A Sociological Study of Market Competition*. Princeton, NJ: Princeton University Press.

Podolny, Joel M. and Freda Lynn. 2009. "Status." In: Hedström P., Bearman P. (Eds.). (2009) *The Oxford Handbook of Analytical Sociology*, Oxford: Oxford University Press (ch. 23).

Price, D. 1976. "A General Theory of Bibliometric and Other Cumulative Advantage Processes." *Journal of the American Society for Information Science* 27:292-306.

Radicchi, F., S. Fortunato, and C. Castellano. 2008. "Universality of Citation Distributions: Towards an Objective Measure of Scientific Impact." *Proc Natl Acad Sci U S A*. November 11, 2008; 105:17268-17272.

Railsback, S. F. and V. Grimm. 2011. *Agent-based and Individual-based Modeling: A Practical Introduction*. Princeton, NJ: Princeton University Press.

Redner, S. 1998. "How Popular is Your Paper? An Empirical Study of the Citation Distribution." *The European Physical Journal B-condensed Matter and Complex Systems* 4:131-34.

Ridgeway, Cecilia. 2011. *Framed by Gender. How Gender Inequality Persists in the Modern World*. Oxford, UK: Oxford University Press.

Ridgeway, Cecilia L. and Shelley Joyce Correll. 2006. "Consensus and the Creation of Status Beliefs." *Social Forces* 85:431-53.

Ridgeway, Cecilia L., Kristen Backor, Yan E. Li, Justine E. Tinkler, and Kristan G. Erickson. 2009. "How Easily Does a Social Difference Become a Status Distinction? Gender Matters." *American Sociological Review* 74:44.

Rigney, D. 2010. *The Matthew Effect - How Advantage Begets Further Advantage*. New York: Columbia University Press.

Rosen, S. 1981. "The Economics of Superstars." *The American Economic Review* 71: 845-58.

Salganik, M. J. and Duncan J. Watts. 2009. "Web-based Experiments for the Study of Collective Social Dynamics in Cultural Markets." *Topics in Cognitive Science* 1: 439-68.

Saltelli, A., K. Chan, and E. M. Scott. (2000)2008. *Sensitivity Analysis*. West Sussex, UK: Wiley.

Sauder, M., F. Lynn, and J. M. Podolny. 2012. "Status: Insights from Organizational Sociology." *Annual Review of Sociology* 38:267-83.

Sen, Amartya. 2009. *The Idea of Justice*. London, UK: Penguin Books.

Shafir, E. and A. LeBoeuf. 2002. "Rationality." *Annual Review of Psychology* 53: 491-517.

Shils, Edward. 1968. "Deference." Pp. 110-147 in *Social Stratification*, edited by J. A. Jackson. Cambridge, UK: *Cambridge University Press*.

Shoham, Yoav and Kevin Leyton-Brown. 2009. *Multiagent Systems: Algorithmic, Game-theoretic, and Logical Foundations*. New York: Cambridge University Press.

Simpson, B., R. Willer, and C. L. Ridgeway. 2013. "Status Hierarchies and the Organization of Collective Action." *Sociological Theory* 30:149, 166.

Skopek, John, F. Schulz, and H.-P. Blossfeld. 2011. "Who Contacts Whom? Educational Homophily in Online Mate Selection." *European Sociological Review* 27: 180-195.

Skvoretz, John. 2013. "Diversity, Integration, and Social Ties: Attraction versus Repulsion as Drivers of Intra- and Intergroup Relations." *American Journal of Sociology* 119:485-517.

Skvoretz, John and Thomas Fararo. 1996. "Status and Participation in Task Groups: A Dynamic Network Model." *American Journal of Sociology* 101:1366-414.

Smith, V. 2008. *Rationality in Economics. Constructivist and Ecological Forms*. Cambridge, UK: Cambridge University Press.

Soll, J. B. and R. P. Larrick. 2009. "Strategies for Revising Judgment: How (and How Well) People Use Others' Opinions." *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 35, 780-805.

Sørensen, Aagen B.. 1976. "Models and Strategies in Research on Attainment and Opportunity." *Social Science Information* 15:71-91.

Sørensen, Aage B. 2001. "The Basic Concepts of Stratification Research: Class, Status, and Theory." Pp. 287-300. In *Social Stratification: Class, Race and Gender in Sociological Perspective* edited by Grusky, David, 2nd edition. Boulder: Westview Press.

Tisue, S. and Uri Wilensky. 2004. "NetLogo: Design and Implementation of a Multi-agent Modeling Environment." http://ccl.northwestern.edu/papers/. Accessed on July 7, 2014.

Todd, Peter M., Francesco C. Billari, and Jorge Simao. 2005. "Aggregate Age-at-marriage Patterns From Individual Mate-search Heuristics." *Demography* 42: 5559-74.

Troyer, Lisa. 2003. "The Role of Social Identity Processes in Status Construction." *Advances in Group Processes* 20:149-72.

Van de Rijt, Arnout. 2013. "Robust Evidence for Cumulative Advantage." Unpublished Manuscript.

Van de Rijt, A., S. Kang, M. Restivo, and A. Patil. 2014. "Field Experiments of Success-Breeds-Success Dynamics." In *Proceedings of the National Academy of Sciences*.

Van de Rijt, A., E. Shor, C. Ward, and S. Skiena. 2013. "Only 15 Minutes? The Social Stratification of Fame in Printed Media." *American Sociological Review* 78:266-89.

Van de Rijt, Arnout, David Siegel, and Michael Macy. 2009. "Neighborhood Chance and Neighborhood Change: A Comment on Bruch and Mare." *American Journal of Sociology* 114:1166-80.

Weber, Max. 1922. *Wirtschaft und Gesellschaft*. Mohr, TX: Tübingen.

Webster, Murray and Stuart J. Hysom. 1998. "Creating Status Characteristics." *American Sociological Review* 63:351-79.

Wilensky, Uri. 1998. *NetLogo Wealth Distribution Model*. Evanston, IL: Center for Connected Learning and Computer-Based Modeling, Northwestern Institute on Complex Systems, Northwestern University. http://ccl.northwestern.edu/netlogo/models/WealthDistribution.

Wilensky, Uri. 1999. *NetLogo*. Evanston, IL: Center for Connected Learning and Computer-Based Modeling, Northwestern University. http://ccl.northwestern.edu/netlogo/.

Wilensky, Uri and William Rand. 2007. "Making Models Match: Replicating an Agent-based Model." *Journal of Artificial Societies and Social Simulation* 10:2. http://jasss.soc.surrey.ac.uk/10/4/2.html.

Will, Oliver and Rainer Hegselmann. 2008. "A Replication That Failed — on the Computational Model in 'Michael W. Macy and Yoshimichi Sato: Trust, Cooperation and Market Formation in the U.S. and Japan. Proceedings of the National Academy of Sciences, May 2002." *Journal of Artificial Societies and Social Simulation* 11:3. http://jasss.soc.surrey.ac.uk/11/3/3.html.

Wooldridge, M. 2009. *An Introduction to Multi-agent Systems*. Glasgow, UK: John Wiley & Sons.

Yitzhaki, S. and E. Schechtman. 2013. *The Gini Methodology. A Primer on a Statistical Methodology*. New York: Springer.

Zuckerman, H. 1977. *Scientific Elite: Nobel Laureates in the United States*. New York City: The Free Press.

Author Biographies

Gianluca Manzo is a research fellow in sociology at the National Center for Scientific Research (CNRS) in France. In his research, he combines computational and statistical modeling to study micro- and interaction-level mechanisms underlying patterns and trends of social inequalities. Sociological theory, in particular action theory and analytical sociology, is also an important part of his work. Currently, he studies the diffusion of technical innovations in nonwestern countries by a combination of field data, network analysis, and computational modeling.

Delia Baldassarri is an associate professor of sociology at New York University. In her research, she uses social network theory and field experiments to address core themes in economic and political sociology. Her recent work focuses on prosocial behavior in diverse societies, public opinion trends in the United States, and how small groups overcome collective action problems.