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Something out of nothing: a Bayesian learning computational model for the social construction of value

Lynette A. Shaw

Center for the Study of Complex Systems, University of Michigan, Ann Arbor, MI, USA

ABSTRACT

This article develops a formalism for the social construction of value. Using a model based on Bayesian agents, it demonstrates how "something" arises out of "nothing" via the emergence of durable value conventions and shows how the developed framework can be used to investigate socially constructed valuations under a variety of circumstances. The resulting analysis clarifies why assumptions that collectives will converge upon the "intrinsic" (i.e., non-socially originating) value of an object (e.g., market efficiency) may not hold for mixed social and non-social valuation regimes, explains the dependency of socially constructed valuations on early accidents, demonstrates the effects of confident actors on constructed values, and identifies the production of time-dependent ratcheting effects from the interaction of bubbles with value conventions.

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1. Introduction

In contrast to "realist" (Zuckerman, 2012) conceptualizations of value as inhering within objects, independent of social processes, "constructionist" (Zuckerman, 2012) perspectives conceive of value as abiding by the Thomas Theorem's (Thomas & Thomas, 1928) assertion that "if men define situations as real, they are real in their consequences" (p. 571–572). In their strongest form, such constructionist models posit an object's value to be exactly equivalent to whatever a group perceives it to be. Though this extreme stance is not necessarily the majority position, the understanding that socially constructed value is an important determinant of economic and social outcomes is a proposition that is widely forwarded by sociologists. Due to a variety of factors, however, the development of a formal framework for exploring this distinctly sociological understanding of value has lagged far behind the equation-based modeling of realist treatments of value that have prevailed within the field of economics for decades.[1] The present work addresses this absence through the development of a parsimonious computational model that allows for a systematic exploration of the emergent dynamics of socially constructed value.

After reviewing the central features of realist and constructionist approaches to value, this article articulates a common basis for both paradigms in their mutual admittance of individual valuation being a process of learning under conditions of initial uncertainty. The next section then shows how this microfoundation (Coleman, 1990; Hedström & Swedberg, 1998) can be readily translated into

CONTACT Lynette A. Shaw shawla@umich.edu Center for the Study of Complex Systems, University of Michigan, 700 Ste. Weiser Hall, 500 Church St, Ann Arbor, MI 48109, USA

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[1]Perhaps the most critical exception to this within economics is the work undertaken within French Conventionalist economics, with the most central example being the program developed by André Orléan (Orléan, 2014). Though the model presented herein was initially developed independently of these earlier models, it can rightly be understood as a reformulation of the "mimetic hypothesis" (Girard, 1965) into a more general microfoundation for collective valuation processes that unifies valuation in both non-social and socially constructed scenarios. Work that has grappled with cross-cultural variance in economic behavior and endogenous preferences (Bowles, 1998) is also highly relevant to the present project.

a parsimonious and generative computational model based on Bayesian updating agents (Epstein, 2006; Hedström & Ylikoski, 2010; Macy & Willer, 2002) that captures the emergent dynamics of socially constructed valuations under a wide range of conditions. The first, central result of this modeling approach will be a demonstration of how socially originating value, rather than being an innately transient or irrational phenomenon, easily achieves the status of a real "social fact" (Durkheim, 1966) or value convention (Biggart & Beamish, 2003; Boyer & Orléan, 1992; Lewis, 1969; Young, 1993) characterized by a durability and stability that resembles non-socially originating valuations. Building from this baseline, the model then clarifies how mixtures of realist and constructionist valuations combine in non-trivial ways that strongly impede a system's ability to arrive at a collective estimation of an object's worth that aligns with its non-socially originating value (i.e., what might be characterized as its "intrinsic" or "fundamental" value in certain perspectives). The final set of modeling results considered then show how this basic model of socially constructed value can be readily extended to systematically explore a variety of other substantively important scenarios in the social construction of value. Among these are a formal clarification of the high dependency of socially constructed valuations on initial conditions, a demonstration of the susceptibility of socially constructed valuations to the influence of highly confident through initially incorrect early actors, and an account for the emergence of "ratcheting effects" in constructed valuations via a fossilization of earlier periods of panics or exuberance within collective memory.

1.1. *Realist versus constructionist approaches to value*

In classical economic treatments, value was often conceived of as inhering within objects themselves via the input of labor and additional production costs required for their production (Ricardo, 1996; Smith, 2003). With the transition to neoclassical economics, understandings of value shifted away from its being an innate property of the object itself toward a reconceptualization of it arising out of an interaction between individuals' personal, subjective preferences (utilities) and the objective availability (supply) of a good (Marshall, 2013). In the first case, value is conceived of as being an objective property of the object itself and in the second, as emerging from an interaction between atomized individuals' subjective preferences and the objective conditions surrounding its availability. As distinct as these approaches are in numerous respect, it is of critical note that in both the "objective" or "subjective-objective" treatments, the influences of social processes on individuals' perceptions of value or the role of social interaction in the constitution and change of individual preferences are not considered[2]

Contemporary work in economics has tackled individuals' valuation processes more explicitly, and in some cases, the potential role of social interactions therein. Several particularly relevant models in this vein are those developed under the heading of the economics of information and include those that grapple with imperfect information and individuals' need to reduce uncertainty in market settings (Rothschild, 1973; Stigler, 1961), information asymmetries in markets (Akerlof, 1970), and information cascades (Bikhchandani, Hirshleifer, & Welch, 1992). Work on information asymmetries in particular has focused on situations wherein sellers have more information on the quality of their product than buyers, with the prototypical example being the used car market and the potential risks buyers face in purchasing as a result. In these cases, interpersonal interactions, including deceit and signaling (Spence, 1973), play an important role in buyers' valuation in as far as they rely on the information gleaned from those interactions to overcome their initial state of uncertainty about the value of the product. Similarly, formal and computational models related to information cascades (Bikhchandani et al., 1992), herding (Orléan, 1995), self-fulfilling prophecies in market contexts (Woodford, 1990; Wyart & Bouchaud, 2007) and the dynamics of bubbles (Harras & Sornette, 2011) also emphasize the role of using socially transmitted information, with the specific focus of such work often being on how social information can lead to widespread *misvaluations* of the underlying object. With regard to valuation under conditions

[2]See (Orléan, 2014) for a more thorough interrogation of these concepts as well as (Bowles, 1998) considerations of endogenous preferences..

of uncertainty and the potential for collective misvaluation related thereto, work on rational expectations (Muth, 1961) is also of important note, specifically as it relates to the efficient market hypothesis (EMH). In this case, a "noisy" process of valuation is admitted wherein individual actors may begin with flawed estimates of a product's value due to having incomplete information on the product being valued. Per this model, however, these individual, random (i.e., non-systematic or correlated) errors in estimation are proposed to cancel out in a manner that allows the market as a whole to arrive at a price of a product that aligns with its "true" underlying value.

These contemporary models have substantially deepened the incorporation of the social in collective valuation. Nonetheless, underlying them remains an understanding of value as originating independently of groups' perceptions of it. Sociological literatures have often conceived of value differently. Specifically, they have traditionally placed much heavier emphasis on the socially constructed or conventional nature of it (Lamont, 2012; Lieberson, 2000; Zuckerman, 2012). From such constructionist points of view, value is not seen as being solely an objective property of an object or a quality that arises from the interaction of an individual's atomized, personal preferences with an object's availability. Instead, it is emphasized as *originating* from shared perceptions of value that arise over the course of social interaction. Said differently, these "intersubjective" perspectives focus on how objects' value are constituted through individuals' assessments of them as having value and emphasize the importance of understanding the processes by which those individual assessment are informed and influenced by others.

In centering the social origins of value, constructionist perspectives have established a venue for exploring the effects of a number of social forces on valuation. Prominent examples include the role of class and power in determining individual preferences and evaluation criteria (Bourdieu, 1984), the reification of valuations that arises from individuals' reliance on other's status as a proxy for quality (Lynn, Podolny, & Tao, 2009; Veblen, 1953), the impact of bandwagon effects in the evaluation of scientific work (Fujimura, 1988) and the fundamental place of cumulative advantage processes in the emergence and persistence of outcome inequality (DiPrete & Eirich, 2006). Other empirical work on valuation in contemporary sociology has also focused on socially driven valuation in cultural production and consumption contexts such as in the case of literature (Griswold, 1987) and art (Dimaggio, 1987), with experimental work undertaken by Salganik et. al. (Salganik, Dodds, & Watts, 2006; Salganik & Watts, 2008) in their series of Music Lab experiments being particularly relevant to the current model. Related work on "socially endogenous inferences" (SEI) (Lynn et al., 2009) and, most especially, recent development and experimental validation of the "Third Order Inferences" (TOI) (Correll et al., 2017) model of valuation, are also of central importance to the development of the current computational model. The subfield of economic sociology has also offered a wide view of how social construction processes affect valuation in real-world economic contexts in ways that lead individuals to deviate from idealized economic behavior (e.g., Carruthers & Babb, 1996; Fourcade, 2011; Krippner, 2001; Zajac & Westphal, 2004; Zelizer, 1994, 2011). Especially relevant to the model under development here is Zuckerman's (2012) afore-referenced considerations of the "pure realist," "pure constructionist," and intermediate classifications of valuation paradigms. Work connected to the French Conventionalist economists (e.g., Boltanski & Thévenot, 2007; Dupuy, 1989; Orléan, 2014) is also highly pertinent, with Orléan's (2014) authoritative treatise on the role of social influence and collective representations of value in the constitution of money and the market dynamics being especially vital.[3]

1.2. *Valuation as learning*

Taken together, these intersubjective approaches to value may appear to address a facet of the world that is distinct from the one being addressed in the objective or subjective-objective perspectives first

[3]Orléan's (2014) discipline spanning work on collective representations of value offers what is perhaps the best bridge currently available between these two value paradigms. The computational model developed here resonates significantly with (Orléan, 1995) earlier model of opinion dynamics orlean1995, with a key difference being this model's formal demonstration that socially constructed value does not require any assumption of the initial existence of an underlying "true" or "correct" value to arise.

reviewed. Underlying these different paradigms, however, is an implicit but vital commonality that provides an essential bridge between them. Chiefly, these approaches prove equally amenable to being conceptualized in terms of a common microfoundation (Coleman, 1990; Hedström & Swedberg, 1998) that of individuals who begin in a state of uncertainty about the value of an object but who, by receiving new information related to it, overcome that initial state in order to make a better determination of its value. Essentially, both paradigms readily admit a straightforward reconceptualization of *individual valuation as a process of learning under conditions of initial uncertainty*. Recast in these terms, the key differences between these two paradigms can then be parsimoniously recharacterized as being not in the valuation procedure itself, but in the sources of information individuals rely upon for that common learning-valuation process. In realist treatments, said information is understood as originating from sources that are fundamentally non-social in nature, though said information may be transmitted *through* social channels with higher or lower levels of fidelity. In contrast, constructionist conceptualizations emphasize situations in which individuals' valuation processes are fundamentally dependent upon information about other individuals' valuations of the object being evaluated.

To ground these ideas in a few simple examples, we might think first about an idealized conception of the value-investment approach to buying stocks. Primary information incorporated into such a valuation/learning process might include research on the quality of the product the company produces, the efficiency of its operations, its physical assets, and what the existing demand for its products is likely to be. The key similarity to recognize is that all of these features are qualities that are assumed to be independent of the valuations that other investors might construct for the company. In point of fact, this class of "valuation opportunism" (Zuckerman, 2012) strategies are directly premised on the expectation that much of the profits to be made from investment will be due to others' incorrect, misvaluations of the company. Given that value learning in this case relies on a set of features which exist objectively and independently of social opinion, the primary task of investors in this scenario is to obtain reliable information on those objective features and correctly anticipate how much each will matter to the long-term profitability of the company. This may not necessarily be an easy task, but it is a relatively straightforward one in this sense that it does not entail complex feedbacks between individuals' valuations of the stock and the true value of the company.

Compare this now against the deeply social scenario of determining the most fashionable outfit to purchase for a high-status event. Here, the objective features of the clothing will not matter nearly as much as one's expectations of how others will ascribe value to it (i.e., the individual will need to engage in making "third-order inferences" (Correll et al., 2017) in order to determine her own preferences). Though two outfits might be of comparable physical quality, individuals invested in being perceived as fashionable will pay a heavy premium for an she expects to be seen by others as being more fashionable or whose brand can be reliably expected to be perceived as high status. Though this might be seen as a relatively trivial example, a comparable logic can just as readily be applied to an individual's valuation of a currency note being fundamentally driven not by their own personal utility for it, but by their expectations of how much others will value it in future transactions (see (Orléan, 2014) for more in-depth considerations of the role of collective value representations and money). In these examples, the inherent, individual preferences an individual has for a pair of shoes or a scrap of cloth and ink are vastly less important than what she has learned about how others are likely to assign value to them. An important feature to note here is that there are many potential pathways through which such social learning might occur. In specific, we can think about how such learning occurs at both the declarative and non-declarative Lizardo levels of individual cognition (e.g., the difference between preferring an outfit as a result of following fashion-related news versus picking up an unconscious taste for a certain clothing esthetic due to being surrounded by others who appear to like it as well). Linking non-declarative pathways of learning-valuation to established literatures in social psychology on evaluative condition (De Houwer, 2007; Gast, Gawronski, & De Houwer, 2012; Hofmann, De Houwer, Perugini, Baeyens, & Crombez, 2010), as well as current work in cognitive sociology on social learning at the level of automatic associative processing (Foster, 2018; Goldberg & Stein, 2018; Shaw, 2015) and the impact of those processes on the formation and application of values (Miles, 2015;

Shepherd, 2017), constitutes a critical line of future development and is the subject of forthcoming experimental work. Regardless of the cognitive level through which such “endogenous preferences” (Bowles, 1998) are being formed, however, the central fact remains that it is ultimately not information on the objective qualities of an object that are relevant to one’s valuation-learning process, but information on others’ valuations.

Though high-level examples like these clarify a fundamental distinction between socially and non-socially originating value, in reality, we can expect there to be many instances in which both social and non-social factors matter to value assessment. One particularly paradigmatic example of this involves the network effects (Katz & Shapiro, 1994) that are a major factor in many communication technologies markets. While a technology such as a fax machine may initially be valued based on its potential personal utility to a user, the determination of its value will ultimately be determined by its level of adoption a process which is fundamentally driven by others’ valuation processes. Along another track, we can also consider how heterogeneity in the valuation models various individuals apply to the same object might also give rise to a mixture of social and non-social information sources in collective valuation processes. A significant example in this regard would be how stocks are traded in many real-world markets. For some, the value-investment model considered above might accurately reflect their valuation process. For others taking a trend following approach to investment, their assessment of the same stock might instead be driven by their expectations of whether others’ valuations of it will continue to rise. We might further anticipate that many individuals will also employ some combination of these two approaches, thereby further increasing the degree to which social and non-social valuation are being mixed together in the collective valuation process.

If the sources of information used in a valuation processes are treated as being less important than the ability of individuals to correctly integrate said information into their learning, the distinction between social and non-social information may be easily disregarded. As will be demonstrated, however, these different origins of value information will prove critical to accounting for differences in emergent macro-level behavior across different valuation regimes. Though an individual’s incorporation of social versus non-social information in his estimation of an object’s value may be exactly the same, the following sections demonstrate show how distinct collective dynamics arise when those individual processes are aggregated under different valuation conditions. It will also demonstrate how, in pursuing a deeper formal engagement with the dynamics of socially constructed value through the general microfoundation of individual processes of learning-valuation, it is possible to derive a unique set of expectations and predictions for the behavior of socially constituted valuation systems that is significantly different from what would be anticipated under realist models of value.

2. A computational model for the social construction of value

Understanding valuation as a process of individual learning under conditions of initial uncertainty establishes a critical link between valuation and a large class of formalisms that have been developed to represent learning. Of these formalisms, one of the most powerful and familiar is that of Bayesian learning. Applying this formalism to the present context enables a translation of the conceptual microfoundation developed above into a computational model based on a learning agent that recursively samples data from its environment to estimate a parameter representing the unknown value of the object under consideration, θ, via a process of recursive Bayesian updating. The following subsections outline how a series of computational models based upon such agents can be designed and used to investigate how the dynamics of socially constructed valuation play out under different information feedback regimes. Though the foregoing represents just one possible path for how the proposed model might be computationally implemented, many of the major, high-level insights that it yields should be expected to hold under a number of other possible implementation designs. Specifically, the model developed herein will relate strongly in its core assumptions to an established class of computational models of social learning and influence (see (Macy & Willer, 2002) and (Castellano, Fortunato, & Loreto, 2009) for reviews) and social construction (Foster, 2018; Goldberg & Stein, 2018; Shaw, 2015).

2.1. *Model design and overview*

This model begins by situating 100 "learning" and 100 "fixed" agents in a system wherein every learning agent has an equal probability of learning from any agent within a predefined population (i.e., all other learning agents, all fixed agents, or a mixture of both). In a given turn of interaction, both fixed and learning agents probabilistically exhibit one of the two states, "up" or "down," that acts as a signal to other agents of the value of the object under consideration. The goal of the learning agents is to use a combination of their preexisting knowledge and their observations of current value signals in order to hone in on an estimate of the object's value, represented by an unseen parameter, θ, that describes the probability with which an "up" (i.e., "valuable") signal will occur, where $(1-\theta)$ describes the probability with which a "down" (i.e., "not valuable") signal is generated. This estimation process can be considered comparable to someone estimating the weighting of a coin using a combination of pre-existing knowledge of it and observations of the number of heads or tails it shows over a series of coin-flips.[4]

For fixed agents, the higher the value of the exogenously specified value of the parameter θ_{fixed}, which can be construed as the "intrinsic" or non-socially constructed value of the object under consideration, the higher the probability they will be in an "up" state on a given turn. Specifically, at the beginning of each turn, fixed agents decide with a probability equal to θ_{fixed} to be in the "up" state for the duration of that turn (with the probability of choosing the "down" state of $(1-\theta_{fixed})$). This setup conceptually maps to the assumption that the greater the value of an object, the more signals it will produce indicating that it is valuable, analogous to a high-quality used car producing more positive evaluations on observable features such as "has good tires" or "drives smoothly." As the sole purpose of fixed (i.e., non-social) agents in these systems is to capture realist perspectives' emphasis on static, non-socially dependent value sources that can be assessed through the observation of the noisy signals produced by it, in all the scenarios considered herein the value of θ_{fixed} remains constant within each simulation run and is the same for all fixed agents. Potential variants of this baseline model in which non-socially generated signals of value are generated by a temporally or population varying θ_{fixed}, however, can potentially have interesting real-world analogs and can be readily developed.

In the case of learning agents, which simultaneously represent individuals undergoing processes of learning-valuation and act as the social sources of information used by other agents in their learning-valuation processes, agent behavior is not driven by a θ_{fixed}. Instead, learning agents base their behavior on their own current *estimated* value of θ. Simple examples of what such positive valuation signals might look like in a realistic context include a person stating to another person that they endorse the object under consideration or expressing a publicly observable willingness to pay an additional premium to acquire it. While the behavior of learning agents is "honest" and "non-strategic" in the models developed here in that all learning agents act in accordance to their current estimates of θ and do not strategically modify their behavior in an attempt to influence other agents' estimates in a particular direction, the introduction of such elements also offer promising directions for future modeling work.

2.2. *Learning agent turn*

Fixed agents do not change their behavior over the course of the simulation run. After being initialized, however, learning agents are left to interact on their own without outside intervention in order to observe the emergent, collective dynamics that spontaneously arise from their individual processes of learning-valuation. For each turn of interaction, all learning agents in the system independently undertake a two-step process in which they first "act" and then "learn."

[4]The assumption of an object's value being represented by a parameter underlying the production of a binomial distribution, and consequent constraining of value signals to be in a binary form, is made here in for the sake conceptual simplicity and to ensure the computational tractability of this initial baseline model. Further development of alternative specifications of this aspect of the model are an important an hopefully fruitful line of future research.

2.2.1. *Step 1: act*

In accordance with standard Bayesian estimation models for binomial processes, agents act according to an implicit assumption that the probability density of θ follows a beta distribution:

$$p(\theta) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)}\theta^{a-1}(1-\theta)^{b-1} \tag{1}$$

Where a and b are shape parameters that respectively reflect the number of "up" and "down" signals previously received, and Γ refers to a gamma distribution.

At the beginning of each simulation run, all learning agents, unless otherwise specified, are initialized with uninformative and weak priors by setting $a_0 = 1$ and $b_0 = 1$ for each learning agent the equivalent of having only observed two signals, one in the "up" state and one in the "down." This initialization allows the model to capture the state of initial uncertainty individuals are posited as beginning with in valuation processes.

In order to act at the beginning of each turn, agents choose to be in an "up" state with a probability equal to the expected value of θ they have based on their current prior distribution for the parameter. For instance, if an agent estimates that $E[\theta] = .8$, it will have an 80% probability in that turn of choosing to be in the "up" state and 20% of choosing to be in the "down" state that turn. Agents calculate this value per the expected value of their current prior's distribution:

$$E[\theta]_i = \frac{a_{it}}{a_{it} + b_{it}} \tag{2}$$

where a_{it} is the initialized shape parameter of agent i, a_{i0}, added to the total number of "ups" observed by that agent from the beginning of the simulation run to the current step, t, of the simulation's run, and b_{it} similarly represents the same for the number of "downs" observed by that agent combined with the initial shape parameter, b_{i0}.

2.2.2. *Step 2: learn*

After the act portion of the turn, learning agents then learn. This begins with agents randomly select without replacement a sample of n other agents in the system and observing the number of agents expressing "ups" vs "downs" in their sample. Under different learning conditions, agents sample from different populations of agents within the system. In the case of purely socially constructed value, agents only sample from other learning agents. In the case of purely non-social valuation, agents only sample from the set of non-learning, fixed agents in the system. In mixed scenarios, agents sample from both populations according to an exogenously specified proportion.

Using the observations from the turn at time t, agents arrive at a new posterior distribution for θ:

$$p(\theta_{it}|y_{it}) = \frac{\Gamma(a_{it} + b_{it} + n)}{\Gamma(a_{it} + y_{it})\Gamma(b_{it} + n - y_{it})}\theta^{a+y_{it}-1}(1-\theta_{it})^{b+n-y_{it}-1} \tag{3}$$

Where n is the number of other agents sampled by the agent in that turn and y_{it} is the count of those agents who were observed in the "up" state. At this point, the recursive aspect of the learning process comes into play as learning agents then make this posterior distribution the new prior distribution for their next round of interaction through the updated shape parameters:

$$a_{t+1} = a_t + y_t \tag{4a}$$
$$b_{t+1} = b_t + n_t - y_t \tag{4b}$$

These updated values are then used to generate the new $E[\theta]]$ that agents will use to determine their action at the beginning of their next turn:

$$E[\theta]_{i(t+1)} = \frac{a_{i(t+1)}}{a_{i(t+1)} + b_{i(t+1)}} \tag{5}$$

2.3. Parameter sweeps

2.3.1. Proportion social

The most important modeling parameter to consider in these systems is the proportion of social to non-social sources of information feedbacks agents have in their observation samples. In the pure non-social case, this proportion will be 0 and agents will only use observations of fixed agents in their learning processes. In the pure social case, the proportion of other learning agents used in learning processes will be 1. In these cases, no observations of fixed agents will occur and thus no globally specified θ_{fixed} value will be present. Between these two extremes are those cases in which agents draw upon a mix of social and non-social sources for their samples. In order to get an understanding of how different levels of social information affect these processes, I sweep through agents having 0%, 20%, 50%, 80%, and 100% of their samples contain other social agents.

2.3.2. Sample size

Given established understanding of parameter estimation processes, a natural expectation is that the size of the samples agents use will impact their estimates. The first pass expectation in this case is that when agents use larger sample sizes, they should hone in more quickly on a stable collective estimate for θ. Furthermore, in non-social and mixed cases where there is a "correct" θ_{fixed} they should be expected to find, the expectation would be that learning agents should converge upon that value more quickly and accurately with a larger n. In order to evaluate these expectations, these simulations consider agent sample sizes between the values of 5, 50, and 100 agents, across individual runs.

2.3.3. Values of θ_{fixed}

In both purely non-social and mixed information scenarios, there exists an exogenously determined parameter for learning agents to find, that of θ_{fixed}. Though learning agents begin with a weak prior (i.e., a weak model of what the distribution of the underlying parameter is), there is still a potential that even this uninformed starting point might influence what arises at the system level. In particular, given that agents essentially begin with a very tentative "guess" that $E[\theta] = .5$, there is a possibility that this starting point might impede the ability of non-social or mixed systems to find values of θ_{fixed} that are far away from that value. In order to account for this potential effect, both the non-social and mixed scenario models include series of runs for three different values of $\theta_{fixed} = \{.2, .5, .8\}$.

2.4. Computationally exploring the social construction of value

Historically, models of social construction have generally relied upon rich, verbal descriptions for their presentation and development. This mode of theorizing has many advantages with respect to features such as the preservation of nuance and richness of meaning. Verbal theorizing runs into significant complexity barriers, however, when it comes to the systematic and principled elaboration of a set of axiomatic assumptions into a set of statements about the world (Ostrom, 1988) – a problem that becomes especially pronounced when the dynamics of interest involve moving from individual level behaviors into collective outcomes (Coleman, 1990; Hedström & Ylikoski, 2010). A primary advantage of the approach developed here is the new

Table 1. Summary of swept values of key modeling parameters.

Modeling Parameter	Swept Values
Total Population Size (P)	100 agents
Proportion Social	***Pure Social***: 0.0
	Pure Non-Social: 1.0
	Mixed: {.2, .5, .8}
Sample Sizes (n)	{5, 50, 100}
θ_{fixed}	{.2, .5, .8}

degree of analytical traction it affords in this regard. The model variants described in the following subsections offer a first pass exploration of how this advantage of the approach can be leveraged to more rigorously evaluate and understand features of socially constructed value under a variety of substantively interesting circumstances.

2.4.1. *Initial conditions and path-dependency in socially constructed valuations*

Per the default protocol of this model, each simulation run is initialized with learning agents choosing to be in the "up" state in accordance with their current estimate for $E[\theta]$, which in the case of the initially flat and weak priors that agents are given, equates to a 50% chance of them choosing to be in the "up". This entails that roughly half of the population should begin a run in either of the two possible states, *on average*. Due to the probabilistic nature of action, however, it is possible for a degree of "accidental" structure to be present at the outset of any given model run in the form of a higher proportion of agents incidentally being in one state or another.

This type of early noise is usually deemphasized in formal models which assume the existence of an intrinsic, "real" value that acts as a fixed attractor for a system to converge upon. In congruence with the emphasis sociological models often place on the high degree of historical contingency and path-dependency in cultural processes, however, this initial incidental structure must be taken seriously in any model attempting to tackle the issue of socially constructed value. This is a feature which makes this phenomena especially well-suited to computational modeling approaches that are better equipped to capture the effects of such stochastically arising, initial structure (Sayama, 2015; Wilensky & Rand, 2015). A more systematic exploration of the long-term effects of initial "accidental" structure in socially constructed value dynamics is made possible through the present model via the exogenous manipulation of the initial configuration of agents. Toward this end, I develop a set of purely social simulation runs in which I force the initial proportion of agents in the "up" state to be at different levels, ranging in value from 0 to 1. Though the initial system state will be set exogenously, all subsequent behavior and learning in these simulation runs is carried out as usual with all agents beginning with the same weak priors as in the baseline model.

2.4.2. *Presence of agents' with initial strong priors*

Another important line of questioning in cases of socially constructed value involves the effect of highly confident though not necessarily correct actors on systems of collective valuation. There are a number of ways this question of potential "value entrepreneurship" (Zuckerman, 2012) could be explored, but for the purposes of the present analysis, the one I consider is a scenario in which there are a few agents who begin the simulation run with a particularly strong model of what θ should be. I operationalize this concept by conducting a series of runs wherein either 1 or 10 agents (i.e., 1% or 10% of the learning population, respectively) begin the simulation with a very strong prior distribution for θ by having them initialized with the shape parameters $a_{strong} = 99$ and $b_{strong} = 1$, the equivalent of beginning the simulation as if having already made 100 observations, with 99 of those observations being of the "up" state. All other agents in the system retain their flat, uninformative starting priors. After this initial setup, the simulation is then allowed to run as usual with both the strong and ordinary agents abiding by standard-established rules for learning and acting.

Of critical note is that this strong prior is technically "incorrect" in as far as it does not accurately reflect the initial estimations of θ of the other agents in the system. We might think of this as reflecting a spillover (Bednar & Page, 2007) scenario in which an individual coming into a nascent valuation system brings with them strong idea of what the collective valuation of the underlying object is based on past experiences in a different group. Conversely, we might also think of this as reflecting a situation in which an individual begins with a strong assertion of what the valuation of an object should be based on their own innate tendency to strongly weight their personal beliefs or a commitment to steer others toward a particular valuation.[5]

2.4.3. *The influence of "animal spirits" in the social construction of value*

Socially driven valuation processes are often linked with the emotional contagions (Hatfield, Cacioppo, & Rapson, 1994) that give rise to widespread panics or manias in economic contexts, and the collective misvaluations which are produced by the influence of such "animal spirits" (Keynes, 1936) on individuals are a long cited source of volatility in markets. These associations often engender expectations that socially based valuations will tend to be characterized by irrationality and instability. In order to sharpen the contrast between these emotionally driven dynamics and the more general dynamics of socially constructed value, as well as to offer an initial exploration of the ways these social processes might interact with one another, I develop a variant of the model which examines the influence of a period of exogenously induced exuberance on collective valuation processes in pure social situations.

To implement this initial exploration, I randomly assign s_{exub} learning agents to a subpopulation, P_{exub}, and have them *act* as if their current learned estimate of θ, $E[\theta]_{it}$, has been increased by a fixed amount, α, for some fixed period of time representing the duration of the emotional contagion's effects, d_{exub}, beginning at an exogenously determined point in the simulation's run, t_{exub}.

Stated more formally, in this variant, if $agent_i \in P_{exub}$ and $t_{exub} \leq t \geq t_{exub} + d_{exub}$:

$$P(agent_{i_{state}} = up)_{t+1} = \begin{cases} 0, & \text{if } E[\theta]_t + \alpha \leq 0 \\ E[\theta]_t \ + \alpha, & \text{if } 0 < E[\theta]_t \ + \alpha > 1 \\ 1, & \text{if } \ E[\theta]_t \ + \alpha \geq 1 \end{cases} \tag{6}$$

2.5. *Modeling outcomes of interest*

The most basic outcome of interest in these systems is the ability of a stable, collective estimation of the underlying parameter to arise from individual learning-valuation processes. This question is particularly important for purely social scenarios given that they do not contain any underlying value of θ_{fixed} to anchor agents' learning processes. To assess this question of convergence, two different but related criteria will be used.

In the case of non-social and mixed valuation scenarios, it is relatively straightforward to define convergence in terms of the system's average estimate of $E[\theta]$ arriving at and remaining near the underlying value of θ_{fixed} that was used in that system run. We can consider this as being analogous to a group of individuals who begin in a state of uncertainty of the value of an object but then, via a process of learning from some combination of non-social and social feedbacks, ultimately arrive at what is traditionally considered the "correct" valuation of it (i.e., the non-socially constructed valuation of it). For the purposes of the present analysis, convergence of non-social and mixed systems is defined as follows:

$$|\theta_{fixed} - \frac{\sum_{i=1}^{N} E[\theta]_i}{N}| < .01 \ for \ c = 50 \tag{7}$$

Where N is the number of learning agents in the system and c is the number of consecutive turns for which this criteria is met. Said otherwise, for fixed and mixed scenarios, convergence will be defined as the point at which the average of all individual learning agents' estimation of the expected value of the parameter has remained within .01 of the actual value of θ_{fixed} for 50 consecutive turns of interaction.

[5]We might consider this a type of "second order" interaction with the collective valuation process wherein an individual understands that their own behavior is influencing others' valuation process and strategically manipulates the information they produce in order to influence it (see Zuckerman's (2012) consideration of "value entrepreneurship" for an excellent example). Due to space limitations, this general class of second-order interactions is not focused on in this work, though the provided model may readily be extended to consider such.

Defining convergence in the social case is more complicated as there is no underlying value of θ_{fixed} for the system to converge upon. For purely social cases then, the focus switches to trying to determine whether or not these systems ultimately settle down into a stable estimation of $E[\theta]$. This quality is assessed using a conservative criteria that compares the changes of the system average of $E[\theta]$ estimates over continuous turns of interaction:

$$\left|\frac{\sum_{i=1}^{N} E[\theta]_{i_t}}{N} - \frac{\sum_{i=1}^{N} E[\theta]_{i_{t-1}}}{N}\right| < .001 \; for \; c = 100 \tag{8}$$

Where t refers to the turn of interaction, N to the number of learning agents in the system, and c to the consecutive number of terms for which the condition holds. This criteria entails that in order for purely social systems to be considered as having converged, the average of the estimated expected values of the parameter across learning agents in the system must remain in a range of .001 for 100 consecutive turns.

For systems which do converge, a question follows concerning how long it takes those systems to reach convergence. By capturing the number of turns that are required for systems to reach a stabilized state, we can gain insight into the overall efficiency of learning in these various systems. In particular, by paying attention to how time to convergence changes in response to proportion of social information feedbacks used, it is possible to gain some insight into the manner in which social and non-social processes interact with one another in mixed scenarios.

In addition to considering system stabilization, where systems ultimately end up in their collective estimation of θ is also of interest. For this, we will be able to use the same average of individual $E[\theta]]$ estimates that was used to establish system convergence. Via this measure, it will be possible to compare the differences between social and non-social learning, the influence of sample size in system learning, the effect of various values of θ_{fixed} in the non-social and mixed cases, and the impact of different social variant treatments. Looking at the variance of estimations across runs of different scenarios will also be useful in thinking about how much variability should be expected across different instantiations of socially constructed vs. non-socially based valuations.

3. Results and analysis

3.1. *Baseline modeling results*

To begin evaluating the difference between social and non-social collective valuation dynamics, I start with results of over 600 pure social simulation runs and 1800 pure non-social runs, with 200 runs for each combination of θ_{fixed} and learning agent sample size n (see Table 1 for overview of swept values). Of foremost note in these results is that all individual simulation runs, both pure social and pure non-social, readily converge. This entails that regardless of the whether or not there was an underlying θ_{fixed} for agents to find, all systems were able to reach a final, stable average estimate for $E[\theta]$ *that accurately reflected the parameter being estimated*. In the case of purely non-social learning, the parameter is that of θ_{fixed}. In the case of purely social learning, the θ being estimated reflects the central tendency of other agents' estimations of θ and constitutes an emergent product of individuals' valuation processes. This constructed quality of the social parameter does not entail that it is any less "real" than the pre-determined θ_{fixed} of the non-social systems, nor does it imply that the average estimate for $E[\theta]$ is somehow inherently "incorrect." Given the known dynamics of social learning and social influence processes, this bootstrapped (Barnes, 1983) nature of convergence in the purely social systems is to be expected (see (Castellano et al., 2009) for an excellent review of the formal properties of this class of systems).

Of greater importance in this context is what this result implies for socially constructed value in as much as we accept the foundational premise that valuation is a process of learning under conditions of initial uncertainty, we must accept that there is no basis for assuming that such socially constructed valuations are *fundamentally* unstable and non-durable. Instead, socially constructed valuations should be understood as being capable of attaining the same stability and durability expected of any other class of convention (Boyer & Orléan, 1992; Lewis, 1969; Young, 1993).

Digging deeper into comparisons across these classes of system, we can also look at time to convergence. Figure 1 shows the distribution of individual simulation runs by modeling parameter condition, with boxes demarcating the edges of the 25^{th} and 75^{th} percentiles of runs.

Unsurprisingly, pure non-social learning systems readily converge upon the values of θ_{fixed} underlying them, even those far away from the weak priors with which agents begin. Of much greater interest in the current context is the fact and timing of the convergence of pure social systems. Pure social systems under the interactional conditions assumed here take somewhat longer than a non-social system to reach the strict convergence criteria defined for them, but not a great deal longer. We can also see that this remains true regardless of whether agents are observing 5%, 50%, or 100% of the population of other learning agents during their learning turns. When contrasted against nave expectations that socially constructed value is not as solid as non-socially based value, this result indicates that such solidity can and does arise in social learning situations as readily as it does in non-social scenarios.

Given that stable collective parameter estimates do arise, another question follows regarding what those final collective estimates were. By definition, the final average of agent estimates of $E[\theta]$ in systems of non-social learning successfully converge upon the underlying value of θ_{fixed}. The result of non-social systems of learning converging upon "true" parameter values is consistent with our understanding of such processes, and consequently, not surprising. More interesting is the question of where systems that begin with no initially "correct" answer to find end up. Figure 2 depicts the distribution of average estimates of $E[\theta]$ in purely social runs. As previously asserted, social systems consistently stabilize on average estimates of $E[\theta]$, just as non-social systems do. This indicates that *within* a given simulation run, no θ_{fixed} is required for convergence. As the wider spread of averages of $E[\theta]$ estimates in Figure 2 indicates, however, the presence of such fixed values does contribute to consistency *across* runs.

Unpacking how purely social systems find an estimate of $E[\theta]$ to converge upon reveals a core feature of socially constructed value. As Figure 2 shows, most systems arrive at an average of $E[\theta]$ estimate that remains near the initial conditions in which such systems began, both in terms of agents' initial estimates of $E[\theta]$ per their weak initial priors as well as to the observable state the system began in roughly 50% of social agents being in the "up" state. Estimates of any given run are still capable of ending up much further away, however, indicating that the fate of the ultimate collective value convention that emerges is not completely bound to individuals' initial, weak priors. The rapidity with which different runs can diverge from one another is

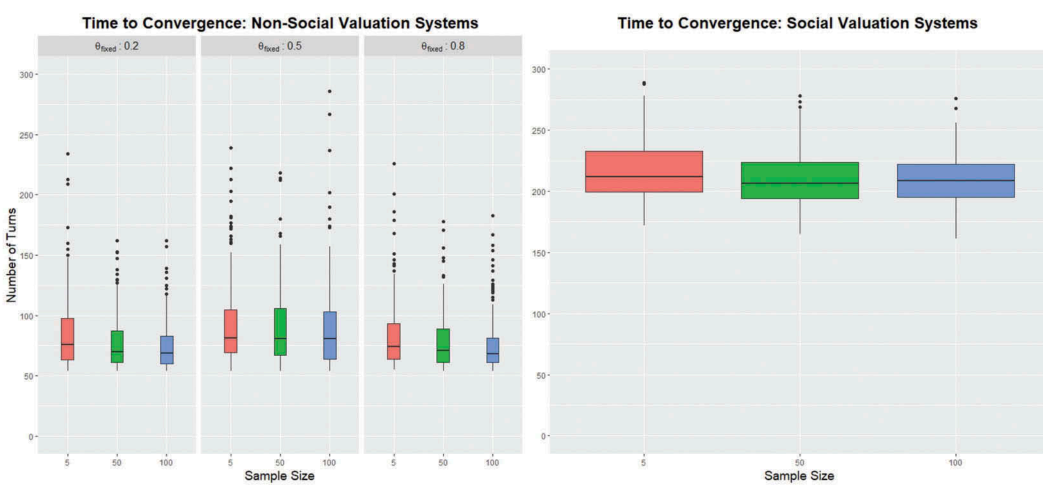

Figure 1. Time to convergence for pure non-social and pure social systems.

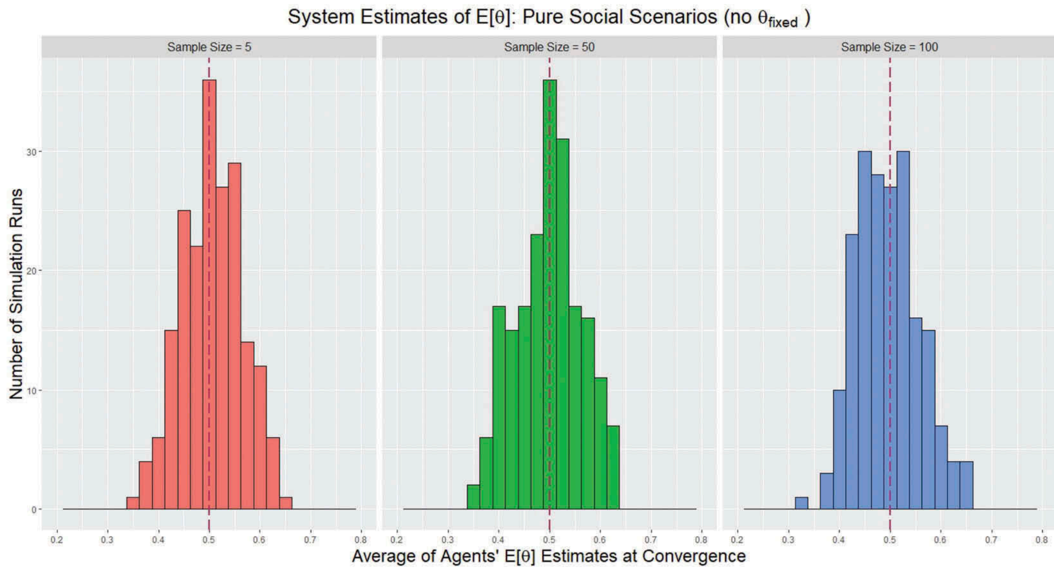

Figure 2. System estimates of $E[\theta]$ (purely social systems).

further illustrated by comparing the average trajectory over the first 200 time steps of the average $E[\theta]$ in purely social systems against the individual trajectories of those systems which ultimately arrived at the highest and lowest average collective estimates of $E[\theta]$, as shown in Figure 3.

Absent a fixed exogenous value to act as an attractor for the system to converge upon, early noise in a pure social system's initial configuration is incorrectly picked up as structure by the learning agents, and in so doing, becomes a kind of emergent, incidental "focal point" (Schelling, 1960) that agents subsequently coordinate upon in their valuation/learning process. As agents adjust their internal model toward the misperception of the presence of structure, their behavior changes to act in alignment with it. This in turn affects other agents' learning. Soon thereafter, the *initially incorrect* guesses at the value of the underlying parameter driving the system are reified and ultimately, *become correct*. This process might be viewed as a type of valuation "symmetry breaking" (Anderson, 1972), a term from complex systems research used to refer to systems wherein final states of the system are not predetermined by structural forces but are instead, ultimately driven by small, incidental fluctuations that occur early in the system's development. This sort of self-fulfilling prophecy (Merton, 1948) or socially bootstrapped (Barnes, 1983) quality of socially constructed value also entails that objects may, *through the valuation process itself*, acquire a stable, collectively adopted, and effectively real level of value without possessing any underlying, non-social source of value.

The systems looked at so far have considered only purely non-social or purely social valuation scenarios. In real-world contexts, however, the value of objects may often arise from a combination of non-social and social sources. This condition can be readily explored with the present model by considering how different proportions of social and non-social information feedback in agents' learning processes impact the emergent dynamics of these systems. Unlike the purely social case, these mixed scenarios represent a return to a situation where there is a presumably "correct" underlying parameter value for the system to find. As such, the criteria for convergence can be conceived of again in terms of systems stabilizing upon this value. Based on many lines of prior work that have explored how the presence of social learning can facilitate collective learning processes (e.g., Boyd, Richerson, & Henrich, 2011; Perreault, Moya, & Boyd, 2012), one might initially anticipate that these mixed condition scenarios should be as good if not better at finding the values

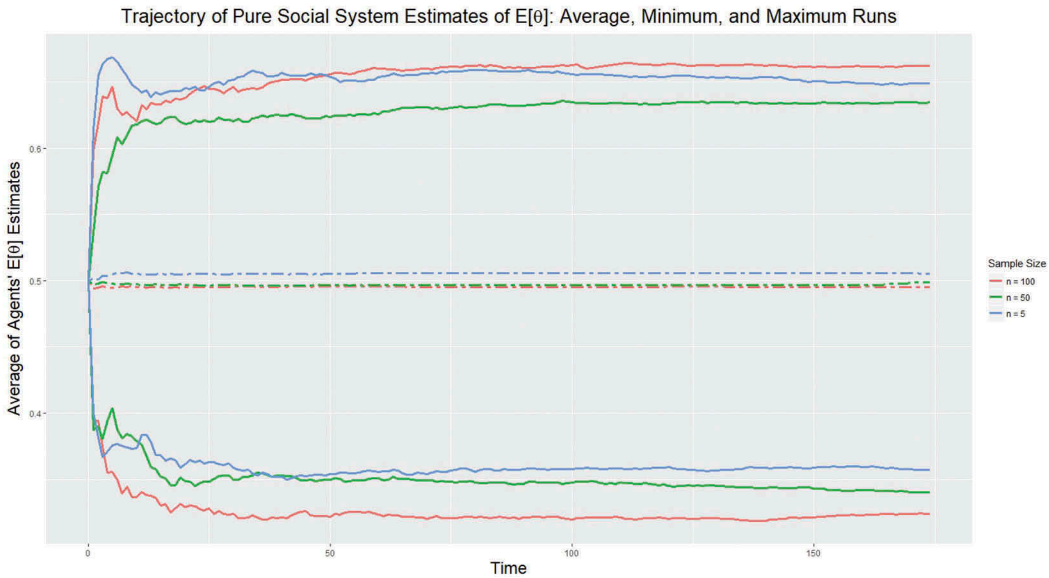

Figure 3. Trajectory of system estimates of $E[\theta]$ (purely social systems).

of θ_{fixed} than the purely non-social scenarios. Furthermore, given the previously explored capacity of early behaviors that are mistaken for structure to influence the development of social systems, one might also assume that the presence of *actual* structure should be as if not more influential on collective valuation processes. Surprisingly, however, this is not the case.

In considering a range of different proportions of social vs non-social information in agents' observations, one of the most striking initial results is that out of 180 exploratory runs of the high proportion social scenarios (i.e., systems where agents' samples contained 80% social to 20% non-social information sources), only 57 converged upon a system estimate close enough to the value of θ_{fixed} to satisfy the previously established convergence criteria before a runtime cutoff of 50,000 turns was imposed. Furthermore, system convergence in these high proportion cases only occurred in situations in which $\theta_{fixed} = .5$, the uncertain estimated value of $E[\theta]$ that learning agents begin near. When θ_{fixed} was a more extreme value, the high proportion social systems were not able to converge upon it in the allotted time.

In the .2 and .5 proportion social situations, systems did converge within the allotted time but did so *orders of magnitude more slowly* than they would have in either the pure social or pure non-social case (Figure 4 notes the logarithmic scale of the y-axis). In congruence with the findings for the high proportion social systems, convergence looks to be easier across the board for systems that have $\theta_{fixed} = .5$. Nonetheless, in the mid-social scenario of 50% social information, we see here an increased variability in how long systems took to find the underlying parameter, especially in situations where the sample size was small. Even more striking are the findings for systems with more extreme value of θ_{fixed}. In these instances, there was a marked increase in the time required to converge upon the underlying parameter, with the most notable effects being the two orders of magnitude increase in time to convergence for systems with small sample sizes.

Qualitatively speaking, in all mixed systems, even the 80% social ones that did not converge before the runtime cutoff, the average of agent estimates of $E[\theta]$ noisily but monotonically approach the value for θ_{fixed}. They did so at an ever decreasing and slowing rate, however, a trend which became more pronounced the higher the proportion of social information present in agents' learning processes. As such, it is not possible to assert that the high proportion systems would never converge upon the underlying value of θ_{fixed}, just that the time it would take to do so

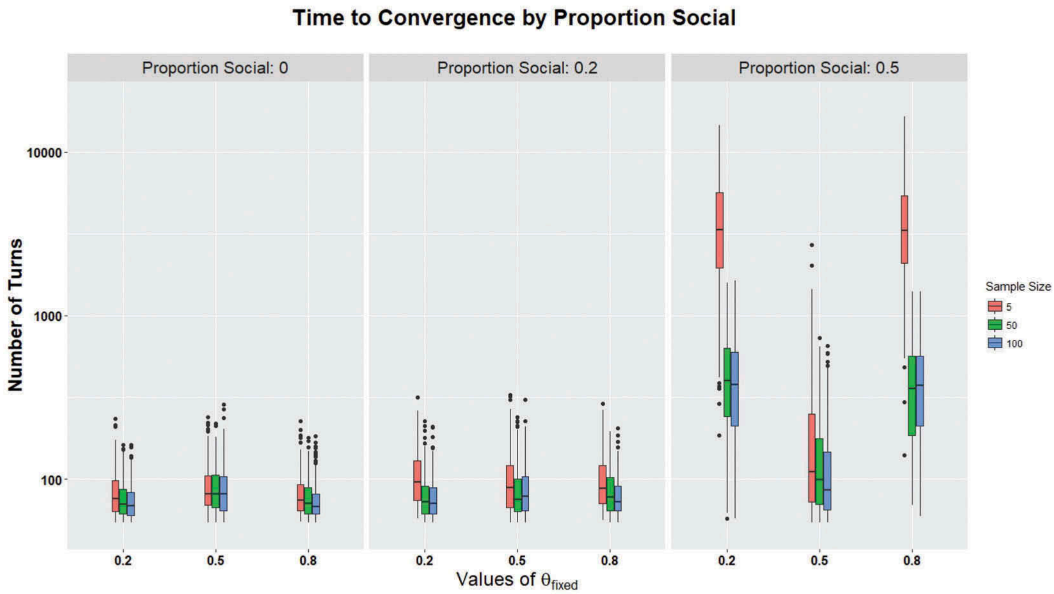

Figure 4. Times to convergence (per pure non-social criteria) by proportion of social to non-social in learning agents' samples.

was more than 2 orders of magnitude greater than in the purely non-social case. Another important point is that if instead of using the criteria for purely non-social systems of successful convergence on θ_{fixed} the convergence criterion for pure social systems was used, many of these slower systems would have been considered as having effectively settled much earlier on a value for θ that did not match that of θ_{fixed}. Given that these systems continued to approach θ_{fixed} after that point, it would not be accurate to say they had fully converged in the strictest sense. Nonetheless, the fact that they ended up meeting the relatively strict criteria for social systems long before they reached the much easier criteria of arriving and remaining within .01 of θ_{fixed} points to a deeper set of considerations regarding collective valuation processes in real-world contexts. Namely, it requires us to seriously consider the question of whether we expect individuals to continue updating their valuation estimates to ever finer degrees of precision or if in practice, they tend to settle on an estimate once it seems close enough to being stable. If the first is the case, then we might expect all social systems to eventually arrive at collective valuation of an object that is "true" in the sense that it reflects only the non-socially constructed aspects of its value. If the second is the case, however, we have grounds for a more inconvenient conclusion that stabilized, real-world valuations may very well be composed of a combination of both the objective qualities of an object and established conventional understandings of its worth.

To summarize, these findings concerning the behavior of systems with mixed sources of learning to carry some strong cautions for our general understanding of valuation processes. Chiefly, they indicate that mixed scenarios cannot be justifiably assumed as being like either the purely social or non-social cases or even as some nontrivial combination of the two. Instead of facilitating the ability of the collective to find values of a fixed parameter, the presence of social learning in these systems exerted the opposite influence, sometimes to quite profound degrees. This realization entails that socially originating information cannot be justifiably assumed away in situations where there is a mix of information being used in valuation processes as their presence can fundamentally alter the dynamics of the collective valuation. Even if such systems may ultimately find their way to the "correct" estimation of an object's value, these results indicate that due to the significant interference arising from even the most straightforward social valuation processes, prevailing assumptions that collectives will ultimately find the "correct" (non-socially originating) value of such objects (e.g., as forwarded by the efficient market hypothesis) must be problematized.

3.2. Results of modeling variants

3.2.1. Initial conditions

The aforementioned sensitivity of pure social systems to early noise and initial conditions, as well as their transition from an early state wherein the collective estimate might potentially take on any number of possible values to the "locking-in" and self-reinforcement of one particular value, are all defining features of path-dependency (Arthur, 1994). The high contingency of such systems' development makes it difficult to predict what any given system will ultimately converge upon, a feature that reflects the indeterminacy of coordination game solutions and the connections which have previously been drawn thereto in work on conventions (Boyer & Orléan, 1992; Young, 1993). Given the present computational approach, getting a better understanding of what factors have an influence on this development is relatively straightforward, especially with regard to disentangling whether it is the initial observable state of the system or the priors agents begin with (or some combination of both) that matters.

Toward the end of explicitly unpacking this issue, I look at the converged outcomes of a series of 6,600 purely social simulation runs where the starting proportion of agents in the "up" state was exogenously forced at the beginning of the run (see Table 2 for values):

Figure 5 depicts the distributions of the average of agents' $E[\theta]$ estimates at convergence for individual social simulation runs under various initial conditions. The most obvious take away from this figure is that the initial starting state of the system strongly affects the ultimate value convention that becomes established within the system. Even though agents begin with the same weak priors as before and no agents' behavior beyond the first turn is determined exogenously, the influence of the systems' state in that single round of initial interaction persists all the way through to final stabilization. This fact provides further support for the proposition that in cases of pure socially constructed value, it is extremely easy for the system to essentially overfit on incidental starting arrangements and subsequently reify them into actual structure. Interestingly, this effect is attenuated for smaller sample sizes, as can be seen in a tendency of systems where agents' had a sample size of $n = 5$ to arrive at estimates closer to the collective estimate of $E[\theta] = 0.5$.

3.2.2. Influence of confident actors

In addition to disentangling the effects of "accidents" in the early history of pure social systems, the current model allows us to investigate the effects of individuals who begin with something other than complete uncertainty of an object's value. Substantively, we might think of this as being analogous to scenarios wherein one or a few individuals at the outset of a social valuation process have strong ideas about what the value of an object should be while the rest of the group begins in the usual uncertain state. Despite the fact that these ideas do not accurately reflect the initial underlying state of the system, these modeling results indicate that the initial certainty and accompanying behavioral consistency of such confident actors can effectively "seed" the social learning process with enough structure to affect where the system ultimately converges, as evidenced in 6 (see Table 2 for prior specification).

Table 2. Pure social variations.

Modeling Parameter	Values Considered
Initial Proportion "up"	0 to 1, .1 increments
Agents with Strong Priors	$s_{strong} = \{1, 10\}$
	$a_{strong} = 99, b_{strong} = 1$
	$E[\theta]_{t=1} = .99$
Exogenous Exuberance	$s_{exub} = 75$
	$t_{exub} = \{50, 200\}$
	$d_{exub} = 50$
	$\alpha = .25$

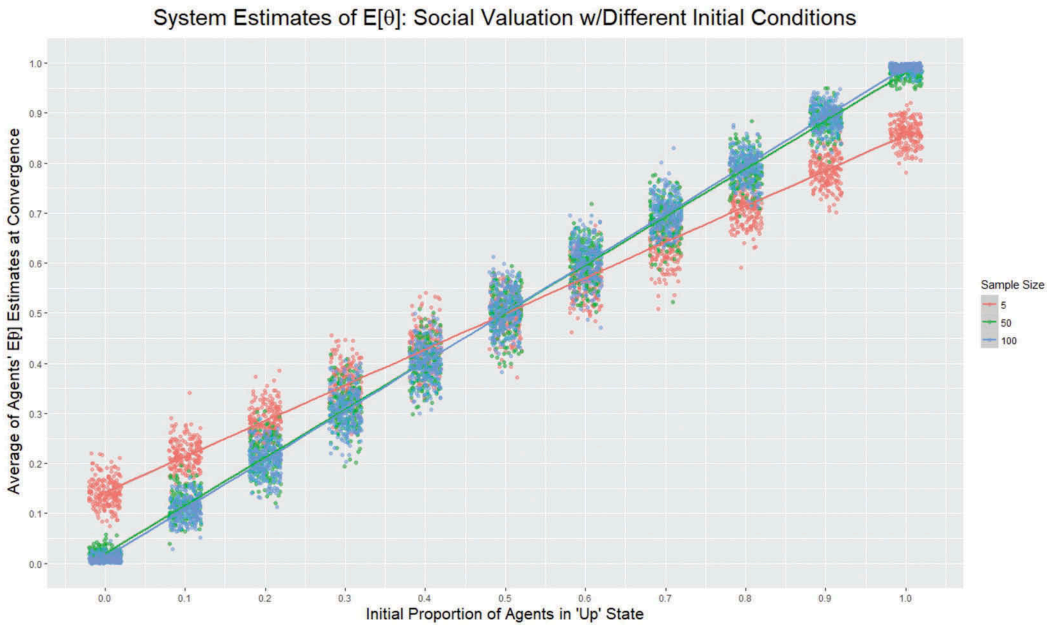

Figure 5. Pure social system estimates of $E[\theta]$ under different initial conditions.

When compared to the distribution shown in Figure 2, the results shown in Figure 6 illustrate how the presence of a small set of agents, or even a single agent, with a strong initial idea of the underlying parameter value can influence where the entire system ultimately converges. In the 800 runs considered in this part of the analysis, the mass of the distribution of where systems' collective estimates for $E[\theta]$ ended up was shifted upward, with the most notable effects being seen in the case of a runs which began with 10% of agents having a strong prior and using a sample size of $n = 5$ in their learning process. While no run got close to the initial estimate of $E[\theta] = .99$ that the agents with strong priors began with, the distribution of runs was ultimately pulled toward that extreme. In all cases, these results demonstrate how in the case of purely constructed valuations, individual actors can have a large influence on the system through no other mechanism than possessing certainty even ill-founded certainty from the outset.

3.2.3. *Animal spirits*

The final pure social variant considered offers a first pass at capturing the effects of periods of collective misvaluation due to extra-learning influences such as one might expect with widespread emotional contagions. The first purpose in developing this extension is to develop a clearer distinction of the irrational dynamics commonly associated with "bubbles" or "panics" from the deeper processes responsible for socially constructed value. In the course of pursuing this distinction, a secondary purpose will be served in accounting for the long-term consequences of these periods on conventional valuation.

As previously described, the modeling variant developed to capture this phenomena involves the exogenous introduction of a period in which a large subpopulation of agents simultaneously have the individual estimates of $E[\theta]$ that are used to determine their behavior in a given turn artificially inflated by some amount α for a short period of time (see Table 2 for values and Eq. 6 for specification). The two example trajectories shown in Figure 7 represent the average trajectories over 200 runs each of the proportion of agents in the "up" state (i.e., behaviorally signifying they

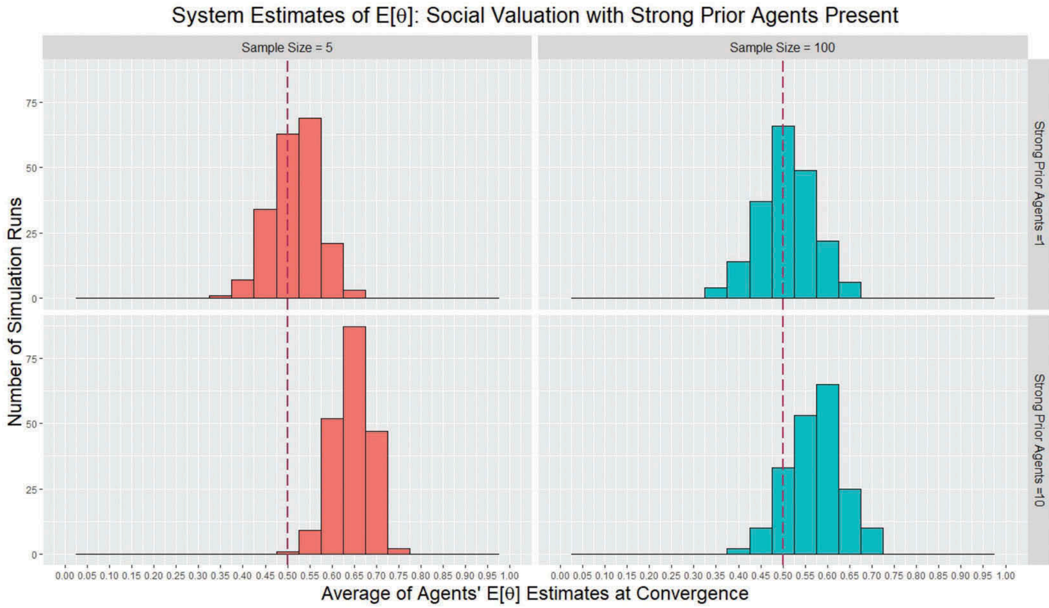

Figure 6. Pure social system estimates of $E[\theta]$ with "confident" agents initially present.

valued the object under consideration) for systems in which agents experienced this artificially induced bubble either "early" or "late" in the system's evolution.

The first feature of note for both bubble scenarios is the clear, behavioral demarcation distinguishing when the bubble begins and ends. Though the extreme sharpness of the transition is undoubtedly an artifact of the discretized nature of the current implementation, it facilitates a clear visual distinction between the dynamics produced from conventional valuation and those which are

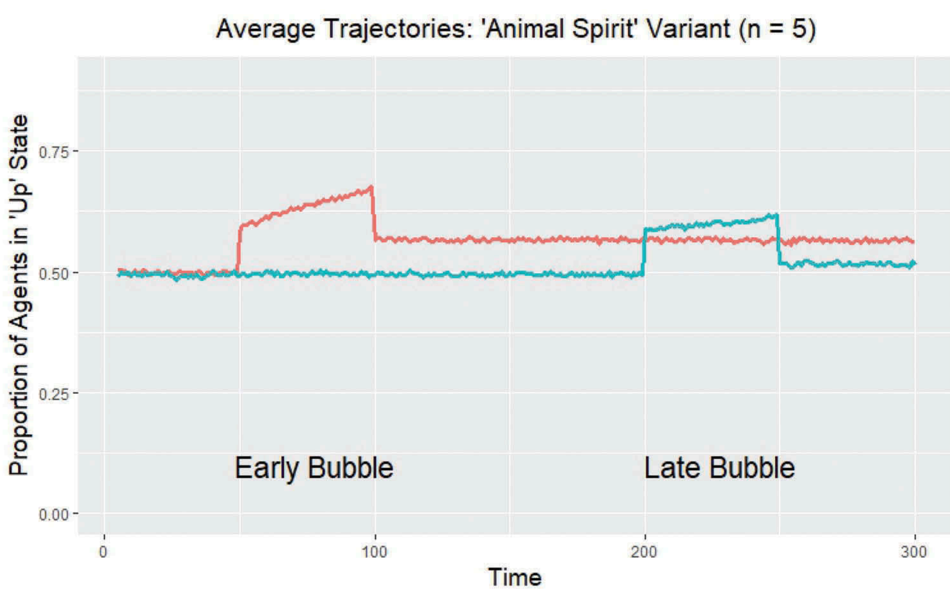

Figure 7. Averaged trajectories across of proportion of agents in "up" state in systems which experienced either early or late, exogenously induced 'bubbles' in valuation (n = 5, 200 runs per condition).

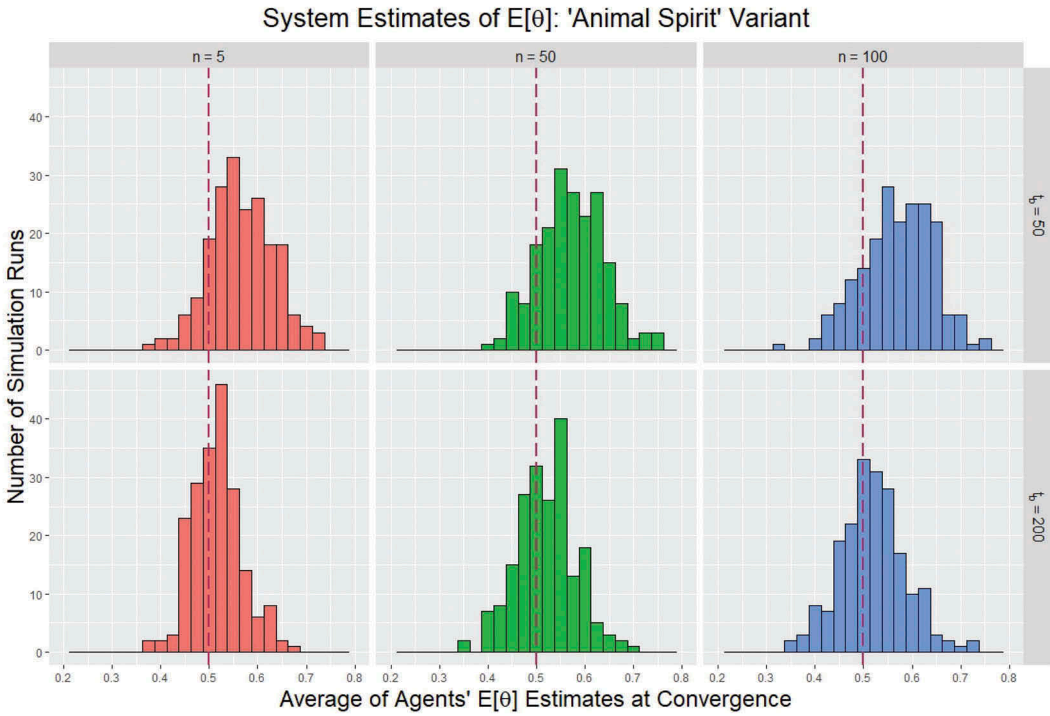

Figure 8. System estimates of $E[\theta]$ of systems experiencing valuation 'bubbles'.

due to irrational, exogenous influences. The primary takeaway from this figure is the clear illustration of how bubbles can occur on top of stabilized, socially constructed values in a manner that qualitatively resembles the "inflation" followed by "popping" patterns commonly associated with collective misvaluations in cases of non-social value.[6]

A feature which is unique to the socially constructed scenario, however, is the "ratcheting effect" produced by the bubble on the long-term conventional value.[7] Though the post-bubble period is marked by a dramatic drop in positive valuation behavior once the exogenously induced influences are removed, these average trajectories indicate that the conventional value of the system reestablished at a level that is higher than where the value was before the bubble, and furthermore, that this increase in the stable conventional value is less pronounced for the later bubble than the early bubble. These results are corroborated by looking at the effects of early versus late bubbles on the ultimate system estimates of $E[\theta]$ (see Figure 8 and the regression analysis results provided in Table 3).

As indicated via the regression analysis of simulation runs presented in 3, when compared to the baseline results of pure social systems which do not experience any exogenous influences on valuation, the presence of an early bubble was associated with a .07 increase in the ultimate conventional value of $E[\theta]$ the system settled upon and a smaller increase of near .02 for the late bubble condition. These long-term effects are a result of the persistence of collective memory in the learning-valuation process, a phenomenon which might be characterized as a "fossilization" of past animal spirits into present conventional valuations. These

[6]An inverse scenario reflecting "panics" through artificially decreasing individual estimates of $E[\theta]$ by some fixed amount would demonstrate a symmetrical dynamic characterized by a "crash" and "recovery" phase.

[7]The initial motivating context for the development of this model engaged with a broader empirical project on the social construction of value vis-a-vis new cryptocurrencies such as Bitcoin. Though far from conclusive, the qualitative resemblance of the ratcheting effect produced by this model and the long-term, qualitative trends in many of these cryptocurrencies' market price is encouraging.

Table 3. Regression analysis of relationship of bubble timing to pure social system estimate of $E[\theta]$.

Parameter	Estimated Coefficient
Intercept	$.500^{***}$
n	-6.28^{-05}
Early Bubble (ref:no bubble)	$.070^{***}$
Late Bubble (ref:no bubble)	$.019^{***}$

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

results also highlight another aspect of socially constructed value's sensitivity to early conditions in that they demonstrate how older, settled systems of conventional value possess a weightier ballast of collective memory to counteract the effects of such transient periods of widespread misvaluation. The implication that follows from this result is that as systems of socially constructed value age, they should be expected to be characterized by decreasing levels of valuation volatility. In effect, traditional valuations become better able to resist the long-term impacts of emotionally fueled fads and panics the longer that they persist.

4. Discussion and conclusion: social construction and its implications for the dynamics of collective valuation

While many models have historically emphasized that *real* value must be grounded in non-socially constituted features of the world, this model demonstrates how intersubjective constructions of value can, over time, become both stable and real in their consequences (Thomas & Thomas, 1928). Notably, it accomplishes this through the articulation of a new, parsimonious microfoundation the unifies historically divergent "realist" and "constructionist" paradigms of value. Rather than being synonymous with transient, irrational deviations from the "correct" estimates of value, it is often treated as being within objective and subjective-objective perspectives, this work demonstrates how socially driven valuation allows groups to arrive at shared, stable assessments of worth without any "intrinsic" sources of value being required. This work has also established, however, that such constructed valuations are not inherently arbitrary in nature but are instead, constrained by the particularities of their developmental histories and the influences of non-socially originating value, as seen for example, in experimentally produced patterns of song quality assessment (Salganik et al., 2006; Salganik & Watts, 2008).

Another implication that receives new formal backing by virtue of this work is the assertion that in strongly social cases, determining the objective, non-social valuation of an object may be nonsensical. For those within and outside the system, the assessment of value in these strongly social situations will be less like researching the innate qualities of an object and more akin to the task faced in Keynes' (Keynes, 1936) beauty contestants game in which individuals are required to anticipate which of the beauty contestants the majority of others will say is most attractive.[8] Said differently, this work demonstrates how in situations of "third order inference" (Correll et al., 2017) in which individuals must develop a reliable assessment of "what everyone knows that everyone knows" (Chwe, 2001; Correll et al., 2017) the value of an object to be, the fundamental challenge faced by those individuals essentially reduces to that of a coordination problem (Schelling, 1960). In so doing, this model provides a potential bridge between the concept of socially constructed value and established formalisms regarding conventions (Biggart & Beamish, 2003; Boyer & Orléan, 1992; Lewis, 1969; Young, 1993) while going further to provide a formal justification for assertions that in

[8]The subsequent variations on this task into *p*-beauty games (Nagel, 1995) in which participants try to guess a number which is some fraction, *p*, of the average of all the other participants' responses to the same task points toward the existence of higher order levels of individual strategic action that take place on top of established conventional valuations. The foundational model developed herein sets aside this level of action for the time being, but it can readily be expanded to accommodate it. The results of such an extension are likely to be relevant to many contexts, including finance, in which an actor is able to strategically manipulate the valuation signals she produces in order to influence the collective valuations of others within the system. For a deeper consideration of this class of activity, see Zuckerman's (2012) discussion of "valuation entrepreneurship".

some cases, it is the stabilized coordination of individual understandings of an object's worth that imbues it with real value and that the correct determination of such an object's value will be exactly equivalent to an accurate appraisal of what most people believe its value to be within a social context.

The results of this model also offer a new, more rigorous clarification of the critical role of time in socially constructed valuations. This work shows, for instance, that asking what the "correct" socially constructed value of an object does not make sense early on in a social system's collective valuation process in the way it does after an emergent valuation has stabilized. This realization of the temporality of socially constructed value also directly connects to other developed insights concerning the sensitivity of such valuations to initial conditions and early actors. Strategically, these results also provide new insights into why those aspiring to influence socially constructed valuations are best served by acting early and with high confidence in the process of collective valuation to make it *seem* as if a particular valuation has become established, regardless of whether that valuation accurately reflects the majority of others' belief at the time. Arguably, these are realizations that propagandists and marketers have been using to great effect for centuries.

While the framework developed herein has sought to formally re-enfranchise the constitutive role of the social in an object's worth, it does not do so at the expense of acknowledging the potential non-social origins of it as well. It is not a pure constructionist model as it does not propose that all value is socially derived, only that social or intersubjective processes are also a legitimate source value. Many sociologists and researchers from humanistic disciplines are likely to agree with this idea in principle without requiring it be translated into an analytical model. The advantage to the computational formalization developed here, however, is that it allows us to move beyond these axiomatic assertions into a more rigorous exploration of how socially constructed value interacts with other types of value that places these established sociological insights into a more direct dialog with the types of formal models that have historically been more favored by realist treatments of the subject (e.g., as seen in the field of economics).

At a broader level, one of the most potentially disruptive aspects of these findings concerns the dynamics that are found to emerge when mixtures of non-social and social sources are involved in collective valuation processes. Specifically, these findings offer a formal clarification of how problematic it can be to naïvely assume that these different information sources will combine in a non-trivial manner. Consistent with prevailing understanding in realist perspectives, these modeling results indicate that sources of non-social value serve as attractors that effectively act as anchors for collective valuation processes. Counter to many of these models, however, these findings demonstrate how the inclusion of social sources in valuation dynamics may have profound implications for the efficiency of that process. Even in the highly idealized scenarios considered herein where factors such as strategic misrepresentation and systematically biased access to information are not being considered, systems relying on a mixture of non-social and social information in their valuation processes took much longer, sometimes orders of magnitude longer, to find the underlying non-socially derived value. These effects are sobering and carry strong implications for models that too readily exclude the constitutive role of the social in valuation or assume that social influences are transient irrationalities that have only a negligible effect on the operation of real-world economic systems.

For instance, in assuming that a market is capable of finding the "correct" (i.e., non-socially originating) valuation of a stock and pricing it accordingly, the profound influence of social valuation is ignored in a way that may not be justifiable. If there is any reason to believe that the potential value of a stock is not only determined by the quality of the assets underlying it but also by what actors in the system expect other actors to value it at (say, for the purposes of being able to sell it later – see Orléan's (2014) discussions of liquidity), then we definitively move from a "pure non-social" to a "mixed" valuation regime. Consequently, the time required for the system to find the true (i.e., non-socially constituted) price of a stock becomes a critical issue and any assumptions that this process will occur in any practically feasible timespan must be called into question. Said more succinctly, this model offers a formal pathway for exploring how readily the invisible hand of the market may be hindered in its movements by shared perceptions of value.

This being said, taking these same results from a different angle clarifies how social influences might be better understood not as deviations from a ground truth but a legitimate, alternative source of value. We might think here specifically of cases in which the worth of goods is not only determined by their immediate utility to individuals but also, by the shared understandings that systematically modify how their worth is collectively perceived. As an example, we can consider the case of products made from recycled materials versus freshly extracted resources. In terms of personal utility, there might either not be a notable difference between the two products or it may even prove that the recycled products are inferior to some degree. However, positive social valuations associated with the recycled product have the potential to increase its value to consumers sufficiently to motivate them to pay a higher price for it.[9] As another example, one might alternatively consider how the high value placed on gold is not due solely to its usefulness in industrial applications or esthetic appeal, but also its generations' long tradition of being highly valued. This greater value is not in any way a mistaken or incorrect assessment of these objects' worth, just one that includes both social and non-social factors in it. In these and a wide class of related cases, this work provides a novel, formal account for why these items' supposedly inflated worth may instead be quite real.

Finally, via its ability to provide a framework for systematically understanding the interaction of collective misvaluations (e.g., animal spirits) with durable, social sources of value, this framework offers a new pathway forward for disentangling the constitutive forces of shared understanding from the effects of more transient social phenomena within economic contexts. As demonstrated in the findings concerning the emergence of temporally dependent "ratcheting effects" in socially constructed valuations, the ability to formally separate these classes of social valuation phenomena not only conceptually clarifies the often conflated distinctions between them, but also, provides a basis for generating new explanations for observed patterns in the real-world valuations of strongly socially dependent objects. A chief example in this arena would be the valuation of currencies – objects whose value is greatly determined by the degree to which perceptions of their worth are shared. Though further development will be required to fully translate this model into the context of currency valuation, the first pass resemblance between the dynamics produced by this model and the ratcheting effects observed in arenas such as cryptocurrency markets is a positive indicator of the potential of this framework to provide a new basis for modeling and researching phenomena that arise at the interface between societies and economies.

4.1. *Conclusion*

Differences in the modeling of substantive phenomena are often less a matter of objective necessity and more of a path-dependent outcome arising from divergent lineages of intellectual development and theoretical practice. In the case of value, there have been long standing and marked differences between how constructionist and realist perspectives have modeled this fundamental concept. The computational model presented herein has sought to offer a bridge across the historical divide that has existed between those literatures concerned with how value becomes real in its consequences through men's definition of it and those aimed toward developing mathematical models of the dynamics of collective valuation. The intention of this endeavor has not been to supplant the rich, and ultimately necessary, qualitative approaches to understanding the processes through which value is constructed that have prevailed to date. Instead, it is offered as a complement to the understanding of such processes in the hopes of further establishing the reality of socially constructed valuations, especially as they relate to economic phenomena. By developing a more formal understanding of how real, stable value is capable of precipitating out of social interaction through the valuation

[9]One might seek to preserve the standard economic view of atomized, individual utilities by saying that the more environmentally friendly product has higher individual utility due to the additional psychic benefits it proffers. This argument belies the strongly social origins of those benefits, however, and misses the point that such increased individual benefit arises in great part from the socially constructed value placed on acting in eco-conscious ways.

process itself, and by demonstrating the wide set of collective valuation dynamic that can be derived therefrom, the present work has aspired to provide groundwork for future theoretical and empirical research into the universe of socially originating valuations.

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