

The Origins of Collective Overvaluation: Irrational exuberance emerges from simple, honest and rational individual behavior

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Abstract

The generation of value bubbles is an inherently psychological and social process, where information sharing and individual decisions can affect representations of value. Bubbles occur in many domains, from the stock market, to the runway, to the laboratories of science. Here we seek to understand how psychological and social processes lead representations (i.e., expectations) of value to become divorced from the inherent value, using asset bubbles as an example. Using an agent-based model we explore whether a simple switching rule can generate irrational exuberance, and systematically explore how communication between decision makers influences the speed and intensity of overvaluation. We show that rational and simple individual level rules combined with honest information sharing are sufficient to generate the collective overvaluation characteristic of irrational exuberance. Further, our results demonstrate that simple noise in the exchange of value information leads to rapidly increasing expectations about value, even when no one is engaged in exaggerating their expectations for the assets they own.

Keywords: decision making; valuation; agent-based modeling; rationality; emergence.

Introduction

Chances are, your savings are invested in one or more kinds of assets—stocks, bonds, real estate, etc. Moreover, if you are an individual investor, or are planning on becoming one soon, you probably discuss the markets with various other investors, including friends, family, colleagues and investment professionals. You might also listen to one of the many market watch programs, or read the business section of your daily newspaper. In short, you are probably engaged in both soliciting and offering opinions on how various market sectors will perform in the future. Once in a while, this information will cause you to make a change in your portfolio. Imagine, for instance, that someone you trust shares with you their expectation for the performance of one of their investments. Imagine further that this expectation exceeds the expectation that you yourself have for your own investments. Surely there is some chance that you would sell (some of) your own portfolio, and invest in the asset with the higher expected return. Whether you would do this naturally depends on myriad other factors—your tolerance for risk, the perceived balance of your

current investments, the liquidity of this new asset class, etc. But there remains some chance that you will make the switch. This is natural, and even—assuming that one of your financial goals is to maximize return consistent with other priorities—rational. But if we are right, this natural, rational behavior is sufficient to spark irrational exuberance.

Asset bubbles are among the most fascinating and puzzling phenomena in economic markets. Decision makers frequently drive up prices and demand to levels that seem completely divorced from the underlying value. Bubbles are common, and far from innocuous. Post-bubble market “corrections” have led to financial ruin for many, as occurred in the great depression and in the current real estate and financial crises. And there seem to be some important similarities between asset bubbles and other sorts of collective behavior, including clothing fashions, popular music trends and perhaps even the trajectory of science (with processes such as paper acceptances and grant funding being based on the expectations of reviewers about the future value of the work). Thus, bubbles are important to understand, to say the least. In the current paper, rather than seeking to understand these events through analyzing or modeling the complex historical and economic factors that lead to a specific instance of collective overvaluation, we have instead focused on formulating some simple and general individual rules that we hypothesize are sufficient to generate the phenomenon of irrational exuberance. We have isolated what we believe to be a key underlying cause of collective overvaluation / irrational exuberance across many contexts, and have constructed a simple model to explore whether it generates the predicted outcomes.

Here we model the genesis of collective overvaluation as a general phenomenon, using decision making about asset classes as an example. We aim to make this model as general as possible, making it potentially applicable to other domains.

Model Description

The model description offered below follows the standardized ODD protocol for describing individual and agent based models (Grimm and Railsback 2005; Grimm et al. 2006). This protocol for describing agent based models has been developed with input from modelers across the disciplines and is in wide use.

Purpose

A commonly observed behavior in markets of many kinds is continually increasing expectations about the future value of certain commodities/asset groups. Here we used agent based techniques to model a simple decision rule that we predict to be sufficient to generate both increasing expectations and overexploitation of certain assets (absorption of all individuals into a small number of asset groups). We also explore the impact of communication fidelity on the outcomes.

State variables and scales

In this model, time and space are both represented discretely. During each time period, all agents execute the commands described in the schedule. The simulation is constructed in a spatial environment for the purposes of visualizing interactions between asset groups.

Process overview and scheduling

This model proceeds in discrete time steps, and entities execute procedures according to the following ordering:

1. Individual A identifies random partner B to be recipient of information about asset value expectations.
2. Individual A communicates current expectation of value for A's current asset class to individual B with some fidelity
3. Individual B adopts expectation of individual A with some probability (opportunism) if A and B come from different groups, and A's expectation is higher than B's.
4. If B has adopted A's expectation then B switches to A's group.

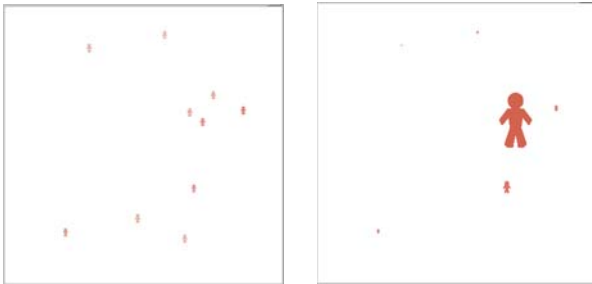


Figure 1: Two screen shots showing the initial conditions and the state of the simulation after 150 time steps under the default parameters (see Table 2). *Left:* The run begins with 10 groups of uniform size with an average expectation of 100. *Right:* After 150 time steps, there is one large group and the expectations of agents have increased to 131.5 (as indicated by the darker red shade of the agents).

Table 1. Overview of state variables associated with each type of entity in the simulation. Bold indicates manipulated independent variables and arrows indicate dependent variables.

Entity	State variable	Description
<i>Global</i>	• Transmission fidelity	Accuracy of communication of expectation. This is modeled by communicating to the partner not the agent's actual expectation, but an expectation taken randomly from a normal distribution with the transmission fidelity as its standard deviation and the agent's actual expectation as its average.
	• Expectation distribution	Initial variability (expressed as Standard Deviation) of expectations among individuals in the population
	• Opportunism	Probability of changing groups given a higher expectation communicated from partner
	➤ Number of groups	The number of groups (asset classes)
	• Number of agents	The number of individuals included in the model
	• Communication target	Binary, either random individual or individual in another group
	➤ Switches per step	The number of agents that change groups each step
	➤ SD switches per step	The standard deviation in the number of switches per step
	➤ Average expectation	The average expectation of all individuals regarding the future value of their investment
	➤ Change in expectation per step	The average change in the average expectation each step
	➤ SD change in expectation	The standard deviation of the change in expectation per step
	➤ Volatility	A combined measure of the SD switches per step and the SD change in expectation per step. This is an indication of the unpredictability of the changes from step to step.
	<i>Groups (Asset classes)</i>	• Location
	• Group size	Number of individuals in asset class
<i>Agents</i>	• Expectation	The future value the individual assigns to the current asset
	• Partner expectation	The information the individual has about their current partner's expectation in their asset class
	• ID number	The identification number of the individual
	• Partner ID number	The identification number of the current partner

Design Concepts

Emergence Irrational aggregate behavior emerged from individual-level rational decision making processes.

Prediction Agents did not have a complex function for predicting the future value of asset classes. They simply adopted information from partners if the information met the conditions described above.

Sensing Individuals have an initial expectation of the value of their asset class based on the expectation distribution. From this point forward, individuals' expectations change only from information transmission from other agents.

Interaction Individuals can transfer information about their expectation of the value of their asset class to partners (with some fidelity). Individuals can move to a new group (asset class), if the partners communicated expectation is higher than the current expectation.

Stochasticity Initial distribution of expectations is randomly distributed around the inherent value of a particular asset class. Opportunistic switching is implemented probabilistically and so has a stochastic element.

Collectives Agents were parts of groups (asset classes) and could transfer information to a 'partner' (from the same or other group). Partners were reset each time period and information transfers were unidirectional (i.e., A might transfer information to B, and B to C)

Observation Simulations were run for 2000 time steps or until only a single group remained. Each combination of independent variables (see Experiments, below) was run 10 times. The dependent variables were measured at the end of each run. Reported results are averages over 10 runs.

Initialization

Table 2 lists the variables associated with various entities in the simulation. All runs were initialized according to default parameters in the table.

Table 2. Initial and default values for all instance variables and independent variables (bold).

Entity	State variable	Initial/Default Value	Units
<i>Global</i>	• Transmission fidelity	Perfect (SD of 0)	
	• Expectation distribution	SD of 10	
	• Opportunism	5%	
	• Number of groups	10	count
	• Number of agents	1,000	count
<i>Groups (Asset classes)</i>	• Group size	100	count
	• Average expectation	100	Expected future value

<i>Agents</i>	• Expectation	Assigned from expectation distribution
	• Partner expectation	
	• ID number	
	• Partner ID number	

Input

This model is designed as a general model of irrational exuberance and collective overvaluation. We did not initialize this model with real world data.

Experiments

We ran three simple and three complex experiments. In the three simple experiments, we used only a single independent variable, while in the three complex we used two, to look for interactions between the effects.

As noted above, all runs were initialized with 10 groups, each containing 100 agents, with an overall average expectation of 100. The three independent variables of interest were: initial expectation distribution, opportunism, and transmission fidelity.

Experiment 1, expectation

This experiment varied only the initial expectation distribution, setting it so the initial distribution of expectations had a standard deviation of 10, 20 and 30. Opportunism was fixed at 5%, and transmission fidelity was perfect.

Experiment 2, fidelity

This experiment varied only transmission fidelity, setting it at 0, 5 and 10. Recall that transmission fidelity is modeled by communicating to the partner not the agent's actual expectation, but an expectation taken randomly from a normal distribution with the transmission fidelity as its standard deviation and the agent's actual expectation as its average. Thus 0 equals perfect fidelity. Opportunism was fixed at 5% and the initial expectation distribution was fixed at 10.

Experiment 3, opportunism

This experiment varied only opportunism, setting it at 5%, 10%, and 15%. The initial expectation distribution was fixed at 10 and transmission fidelity was perfect.

Experiment 4, expectation x fidelity

This experiment varied both expectation distribution (10, 20, 30) and fidelity (0, 5, 10). Opportunism was fixed at 5%.

Experiment 5, fidelity x opportunism

This experiment varied both fidelity (0, 5, 10) and opportunism (5%, 10%, 15%). The initial expectation distribution was fixed at 10.

Experiment 6, expectation x opportunism

This experiment varied both expectation distribution (10, 20, 30) and opportunism (5%, 10%, 15%). Fidelity was perfect.

Dependent variables

The dependent variables measured in these experiments were:

- The average expectation at the end of the run, representing the average agent expectation of the value of the asset class(es).
- The number of groups remaining at the end of the run, representing the number of asset classes with investors
- The number of switches per step, corresponding to the number of agents that switched groups each time step
- The average change in expectation per step, corresponding to the change in expectation that occurs as agents switch and adopt the expectations of others
- The volatility of the system, measured as the summed standard deviations of the number of moves per step and the average change in expectation per step.

Results

Descriptive statistics for experiment 1, expectation, are listed in Table 3. Increasing the distribution of expectations lead to a higher average expectation at the end of the run (ANOVA, $F(2, 27) = 112.45, p \ll .01$, see Figure 2) a larger change in expectation each time period (ANOVA, $F(2, 27) = 58.31, p \ll 0.01$), and higher overall volatility (ANOVA, $F(2, 27) = 34.34, p \ll 0.01$).

Table 3. Descriptive statistics for experiment 1, expectation.

Expectation distribution:	10	20	30
Groups at end	1.0 (0.0)	1.0 (0.0)	1.0(0.0)
Average expectation at end	131.55 (4.34)	165.99 (10.44)	199.95 (13.57)
Number moves per step	11.65 (2.25)	12.18 (0.92)	12.13 (1.31)
Δ-expectation per step	0.09 (0.02)	0.21 (0.04)	0.29 (.0.6)
Volatility	10.81 (0.52)	12.21 (0.47)	12.85 (0.68)

Descriptive statistics for experiment 2, fidelity, are listed in Table 4. Greater noise (low transmission fidelity) led to much higher average expectations at the end of the runs $F(2, 27) = 68.66, p \ll .01$ (see Figure 3); to more groups at the end of the simulation $F(2, 27) = 91.5, p \ll 0.01$; and to less overall volatility $F(2, 27) = 521.56, p \ll 0.01$.

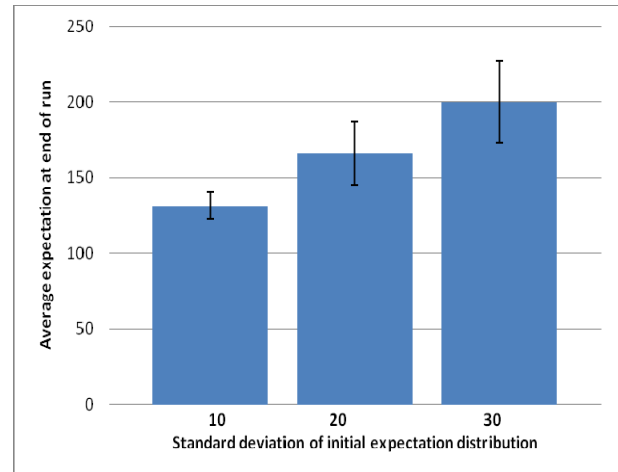


Figure 2: Increase in average expectation as a function of initial expectation distribution. Error bars represent ± 1 S.E.

Table 4. Descriptive statistics for experiment 2, fidelity.

Transmission fidelity:	0	5	10
Groups at end	1.0 (0.0)	3.3 (0.48)	2.7(0.48)
Average expectation at end	133.84 (2.86)	375.31 (107.04)	682.72 (146.98)
Number of moves per step	12.67 (1.23)	17.88 (0.68)	17.90 (1.30)
Δ-expectation per step	0.11 (0.02)	0.25 (0.01)	0.49 (0.02)
Volatility	10.94 (0.51)	5.68 (0.17)	6.57 (0.40)

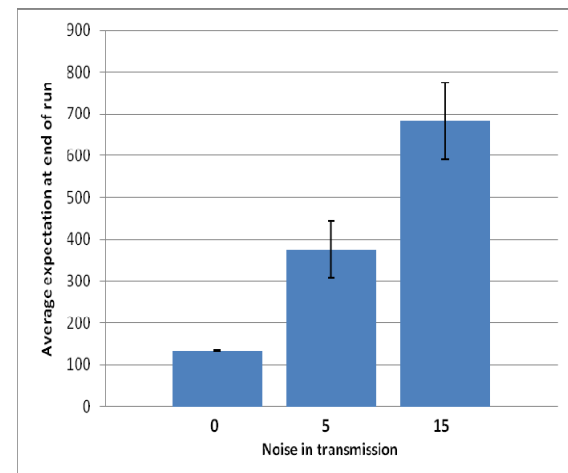


Figure 3: Increase in average expectation as a function of transmission fidelity. Error bars represent ± 1 S.E.

Note the increase in expectation is driven in part by the fact that with high noise, the number of groups never drops to one, as it always does when fidelity is perfect. Thus the

simulations when fidelity was > 0 lasted for all 2,000 steps, rather than stopping after around 300 steps, as is typical when fidelity is perfect. Even so, there was also a significant increase in the average change in expectation per step, indicating that the effect is not simply a matter of running the simulation for longer.

Descriptive statistics for experiment 3, opportunism, are listed in table 5. Greater opportunism increases the number of moves per step $F(2, 27) = 657.16, p < 0.01$; increases the amount by which expectations change each step $F(2, 27) = 657.16, p < 0.01$; and increases volatility $F(2, 27) = 1531.22, p < 0.01$. In addition, there was a decrease in the number of steps it took to achieve one group, and thus for the simulation to end $F(2, 27) = 260.41, p < 0.01$. That is, the more opportunistic the agents are, the faster the collective converges on a single asset. This explains why, despite a significant increase in the change in expectation each step, there was no main effect on average expectation at the end.

Table 5. Descriptive statistics for experiment 3, opportunism.

Opportunism:	5%	10%	15%
Groups at end	1.0 (0.0)	1.0 (0.0)	1.0(0.0)
Step when one group reached	298.80 (30.68)	162.30 (14.86)	98.70 (6.46)
Average expectation at end	133.45 (4.71)	132.21 (2.49)	133.76 (3.35)
Number of moves per step	12.71 (1.07)	25.33 (1.83)	38.73 (1.80)
Δ-expectation per step	0.11 (0.02)	0.20 (0.01)	0.34 (0.04)
Volatility	11.09 (0.41)	21.02 (1.22)	31.95 (0.69)

Interactions

The three complex experiments revealed the same main effects, which won't be repeated here. Instead we'll simply summarize some of the significant interactions.

Experiment 4, Expectation x Fidelity reveals a significant interaction between expectation distribution and fidelity on volatility $F(4,81) = 3.42, p = 0.012$. Whereas the general effect of fidelity on volatility is to decrease it when going from 0 to 5, and increase it slightly when going from 5 to 10, this latter effect disappears at higher levels of expectation distribution.

Experiment 5, Fidelity x Opportunism reveals an interaction between fidelity and opportunism on the number of moves per step $F(4,81) = 21.66, p < 0.01$; the change in expectation per step $F(4,81) = 341.86, p < 0.01$; and volatility $F(4,81) = 256.84, p < 0.01$. Both fidelity and opportunism increase the number of moves per step, and increase the change in expectation per step, and together the higher values increase the magnitude of the effect. As noted above, the change in fidelity tends to decrease volatility

initially, then increase it slightly. These effects are greater as opportunism increases.

Experiment 6, Expectation x Opportunism reveals an interaction between expectation distribution and opportunism on the change in expectation per step $F(4,81) = 15.40, p < 0.01$ and on volatility $F(4,81) = 10.71, p < 0.01$. In each case the tendency of the independent variables to increase volatility and change in expectation per step is enhanced at higher levels of the other variable.

Discussion

On December 5, 1996, after nearly fifteen years of steady growth in the S&P 500 and Dow Jones Industrial Average (and just before the record-breaking bull market to follow), Federal Reserve chairman Alan Greenspan expressed his concern that the behavior of the stock market was characterized by "irrational exuberance". Whether he was right or not, it is certainly true that the price to earnings ratio had by then surpassed 27, a level that hadn't been seen since 1929, and was on its way to the record high of 47 it achieved in March of 2000. What leads to this sort of (apparent) disregard for underlying real value? There are several possible explanations. Some favor accounts based on individual irrationality—e.g. "animal spirits" like (over-) confidence and our tendency to be influenced by nominal amounts of money—that can be amplified under certain market and social conditions (Akerloff, 2005; Akerloff & Shiller, 2009). Others favor "herd behavior" models in which individuals allow their choices to be guided by other people's choices, on the (reasonable, but by no means certain) assumption that there is wisdom in crowds (Surowiecki, 2004). On these models, observations of early choices create an information cascade that causes late choosers to follow early ones, rather than following their own signal (Banerjee, 1992; Bikchandri, Hirshleifer & Welch, 1992). Finally, there is currently a great deal of discussion of the role of deception in the recent real-estate bubble (Bitner, 2008).

Here we consider the alternate possibility that irrational exuberance is driven by neither irrationality nor deception, nor requires individuals to ignore their own information and preferences, but instead emerges from simple, honest and rational individual-level behavior. To explore this possibility we created an agent-based model where agents have simple and seemingly rational individual-level rules for switching between asset classes and updating their representations of asset value based on information from others. Our results show that a simple rule—when another agent's expectation for the performance of their investment exceeds your own expectation for your own investment, consider switching investments—can generate collective behavior resembling irrational exuberance.¹ In particular,

¹ Although communication partners were chosen at random, agents adopted new expectations *only* when the partners represented different asset classes. Restricting communication to partners from other groups greatly speeds the dynamics outlined here, because members of smaller groups are bombarded with

we see rapidly increasing expectations for the value of commodities and the overexploitation of a single asset class. Further, our model shows that this collective overvaluation can occur even when there is no individual deception or bias in favor of exaggerating value when communicating to others about it. This suggests that surprisingly simple and rational individual level rules can generate some of the complex and irrational aggregate outcomes associated with market bubbles.

One especially interesting finding was the massive effect that transmission fidelity had on overvaluation. Here is a system in which increasing noise increases the rapidity and magnitude of overvaluation, and the interactions demonstrate that this effect can be magnified by other factors. Ironically, then, Alan Greenspan's infamous opacity could itself have been a contributor to the irrational exuberance he warned against. Although we do not explore this possibility explicitly here, it is clear that combining noise with even a few agents intent on deception would cause even greater overvaluation than we demonstrated in these experiments. This is perhaps part of the combination that led to the recent real-estate bubble.

This model has both specific implications for the phenomenon of market bubbles as well as general implications for the phenomenon of collective overvaluation across domains. Because this model simulates individual decision making processes (as is typical of agent based models) rather than simply aggregate dynamics, it is able to capture important effects of interactions among individuals (in terms of information sharing and switching). Models such as this can be used to improve our understanding of the psychological and social components of decision making behavior by allowing us to explore the generative sufficiency of individual rules as well as the sensitivity of the system to alterations in parameters such as those explored here (i.e., transmission fidelity, initial expectation, opportunism in switching). The model presented here demonstrates that representations/expectations of value can become dissociated from inherent value when individuals use simple and rational decision rules combined with well-intentioned communication. The emergence of increasing expectation from these simple and general decision making and communication processes may be the fundamental principle that gives rise to irrational exuberance, not just in the market place, but in any domain in which individuals switch from their current option when they hear about better opportunities elsewhere.

Thus, in addition to the potential relevance of this model for market phenomena, there are more general implications that can be drawn as well. The emergence of collective overvaluation from a simple switching rule could occur in a wide range of domains, making this model applicable to a wide range of phenomena. In fact, this model is sufficiently abstract that it can be applied to a variety of other situations in which individuals' assessments of value are based on

social information. For example, clothing fashions, popular music, and even current trends in areas of scientific study might be subject to similar processes. These may be fruitful avenues for future research.

Future work will also explore market dynamics in greater depth and detail. For instance, we will explore the effect that broadcast information (e.g. announcements from the Fed, ratings agencies, etc) might have on the creation of asset bubbles. We will also allow for the dynamic creation of new asset classes, and allow agents to decide to temporarily opt out of the market. Finally, we will explore what can be done to reverse such overvaluation in a more controlled fashion than is typical in a market crash, or prevent high degrees of overvaluation from occurring in the first place.

Acknowledgments

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messages from members of larger groups, thus increasing their likelihood of switching to the larger group.