Market bubbles and investor psychology

Vanguard research

February 2011

Author
Stephen P. Utkus

Executive summary. One of the distinctive features of the past decade was the formation and collapse of two financial market bubbles—one in internet stocks and a second in the housing and mortgage finance system. This paper outlines a model of market bubbles from a behavioral finance perspective, highlighting their psychological origins. The main elements of the model include: (1) initial errors in forecasting the future based on the representativeness heuristic; (2) the emergence of excessively rosy forecasts because of overconfidence and excessive extrapolation; (3) the amplification of skewed positive forecasts across a financial market through group polarization; and finally (4) the resetting of those forecasts to an excessively cautious level in the subsequent market crash.

The paper also outlines several techniques to help mitigate bubble psychology, including increasing investor experience, managing emotions, "widening the frame" for investment decisions, and using external and independent sources of information to calibrate judgments.

Introduction

One of the distinctive features of the past decade was the formation and collapse of two major asset bubbles in the financial system. The first emerged in technology, media, and telecommunications (TMT) stocks—the so-called internet or Nasdaq craze of the late 1990s. The second occurred in the mortgage financing system and was characterized by a rapid rise in housing prices, surging household and financial system debt levels, and a subsequent retrenchment in prices and housing finance. The collapse of the mortgage bubble was associated with the worst economic downturn since the 1930s.

These two financial bubbles have a number of well-known historical precedents, including manias for Dutch tulip bulbs in the 1630s, South Sea land in the 1720s, and U.S. stocks in the 1920s.[1] One of the unique features of the recent market bubbles is that they occurred in a period of rapid evolution in the technology of global financial systems. This evolution has included advances in statistical modeling, widespread availability of market data, new market instruments to hedge risk, and a rising level of financial sophistication among many market participants. Yet two substantial bubbles emerged, despite—or, perhaps, because of—this meaningful increase in the sophistication of financial markets and systems.

A number of causes are commonly given for the rise of speculative excesses in a financial market. These include misaligned incentives, lack of investor sophistication or experience, and fraud. For example, explanations for the recent mortgage crisis in the United States have included: excessive profit-seeking by mortgage originators, bankers, and rating agencies; a lack of institutional investor or homeowner foresight in evaluating the risks of mortgage instruments; differences in sophistication or experience between mortgage originators and homeowners, or between underwriters and investors; misaligned incentives for government-sponsored mortgage agencies; and alleged fraud and deception by various parties in the mortgage process.

In this paper, we take a different tack and formulate a model of market bubbles and crashes based on psychological traits drawn from behavioral economics. Our aim is not to supplant other explanations, but to consider the psychological origins of bubble behavior. Behavioral economics attempts to augment rational models of decision-making with psychological factors. Our goal in this paper is to specify ways in which psychological characteristics might be factors in extreme fluctuations in market sentiment, contributing to the formation and collapse of bubbles. These elements may explain why market bubbles persist even in the face of rational advances in the technology and systems of finance—and explain how such systems might actually amplify these tendencies.

This paper, after defining the concept of a bubble, presents a four-stage model for the formation and collapse of asset bubbles. It uses the recent U.S. mortgage crisis as a case study. A concluding section considers implications for the investment community —including institutional and individual investors, advisors and consultants, and the financial media.

Defining a bubble

An asset bubble can be defined as a substantial difference between an asset's current price and its intrinsic value. A bubble is characterized by a rapid, often accelerating increase in the price of the asset, followed at some point by a precipitous decline. Although this definition seems straightforward, it is inherently difficult to apply because fundamental values are not observable. Intrinsic values can only be estimated, and there can be widespread disagreement over such estimates at any given time.

It is also hard to distinguish a bubble from ordinary price fluctuations associated with fundamental market or economic factors. In retrospect, it seems clear that stock prices in 1929 and in 1999 were at extreme levels of valuation.[2] The same could be said of U.S. housing prices in 2007. Within the stock market, there are also times where particular sectors seem to experience what look like fads or manias—such as the rise (and subsequent fall) of the "nifty 50" growth stocks of the late 1960s and early 1970s.

Yet while the "nifty 50" stocks contributed to a market bubble in the early 1970s, the subsequent fall in stock prices—the bear market of 1974–1975, when stock prices fell by half—was also linked to specific changes in macroeconomic conditions. A large part of the market decline seemed rationally

1 See Chancellor, 2000; Kindleberger and Aliber, 2005; and Mackay, 1841, 1980.

2 For example, Campbell and Shiller, 2005, documented the extreme valuations in U.S. stocks at their peak in 1999 and in early 2000 and predicted poor future returns.

linked to the sharp rise in the global price for oil and an expected slowdown in the global economy—not solely to a bubble bursting. Similarly, while stock prices might have been considered overvalued in 1987, their large decline in October 1987 could be at least partially explained by the then-current environment of rising interest rates. In other words, there are always periodic corrections and bear markets in equity prices. While some might be characterized as a collapse of a market bubble, others seem rationally linked to changing economic and market conditions.

In the end, defining a bubble appears to depend on how extreme the valuation measures and the price changes are. Any such judgments seem clearer in retrospect. From this perspective, a short list of U.S. financial bubbles would include stock prices in 1929 and 1999 and housing prices in 2007. Other candidates in equity markets might include 1987 and the early 1970s. In this sense, market bubbles across a major part of the financial system may be quite rare.

Thus, from the perspective of the model in this paper, the difference between a bubble and crash scenario versus the more common bull and bear phases of a market may be only a question of degree. In bubbles and crashes, the psychological biases discussed in the model may simply reach more extreme levels.

The model

Our model of bubble behavior consists of four stages (Figure 1). In Stage 1, investors develop initial forecasts of asset prices based on errors in statistical inference, broadly captured under the idea of the representativeness heuristic (where "heuristic" means a decision shortcut). In Stage 2, these forecasts of future price appreciation become exaggerated. Overconfidence and excessive extrapolation of recent positive experience come into play. In Stage 3, individual forecasts influence the behavior of the group (in this case, the market or financial system as a whole). Through a process known as group polarization, the financial system takes on higher risk exposures than individual members would separately agree is prudent. Finally, in Stage 4, as actual market data begins to undermine the group's overconfident forecast of the future, the group polarization process plays in reverse, and the collective market outlook shifts sharply to the negative.

Stage 1: The initial forecast

Within a financial system, embedded in the separate decisions made by households and institutions is a set of forecasts about the future. Each forecast represents an expected evolution of future events, whether relating to stock prices, home mortgages, or other capital assets.

Indeed, all decisions, whether financial or not, can be viewed as being based on a forecast of expected future value, whether those decisions are relatively trivial (such as whether to have coffee or tea as a breakfast drink) or highly consequential (such as making investment decisions, choosing a career, or pursuing a relationship). Underlying any decision is a forecast that one particular path—this morning's drink, this degree, this job, this person—will lead to higher satisfaction than another path. What is true for individuals is equally true for institutions.

In the case of financial markets and financial decisions, these separate forecasts of the future may be *ad hoc* and intuitive, developed informally in the minds of decision-making agents. For example, in the case of stock market expectations, an intuitive

Figure 1. Four-stage model of market bubbles

Stage	Behavioral heuristics	Characteristics
1. The initial forecast	Representativeness heuristic	Forecasts of future asset values are developed with embedded errors in statistical inference
2. Overconfidence	Overconfidence, excessive extrapolation	Future forecasts become excessively rosy and are skewed to the positive, especially based on recent experience
3. Group transmission/ amplification	Groupthink, group polarization	Overly optimistic forecasts are widely disseminated and lead the group as a whole to higher risk-taking levels
4. Recalibration	Group polarization	Forecasts are deflated by actual experience and revised downward rapidly and beyond realistic values

Source: Vanguard, 2011.

forecast might be: "I anticipate that stocks will provide higher returns than bonds over time." Forecasts may also be stated formally as expected average values or a statistical distribution, representing a range of future outcomes. For example: "I believe that the equity risk premium will average 6% per year," or "Stocks are expected to offer a return of 12% with a standard deviation of 20%."

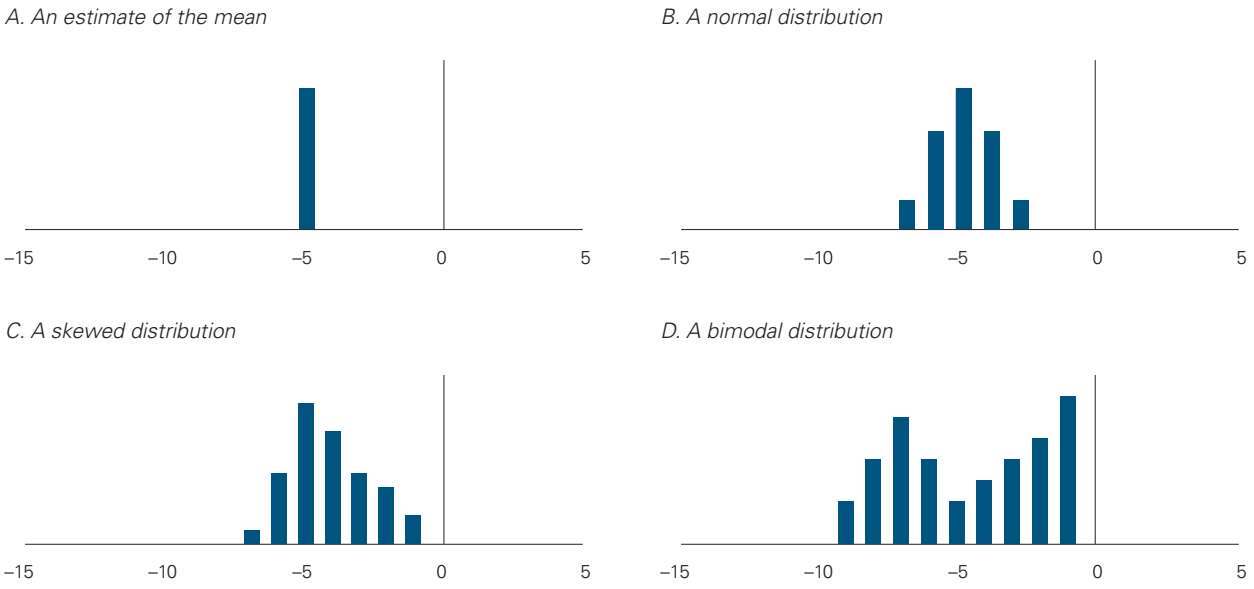
Consider the case of mortgages. As part of the process of assessing mortgage securities, suppose an analyst for an underwriter or credit rating agency estimates a simple average default rate on mortgages of 5% (Figure 2, panel A).[3] This estimate could be more formally stated as a normal statistical distribution (Figure 2, panel B) or a skewed distribution, where the expected default rate is less than 5% (Figure 2, panel C). It could even be a bimodal distribution, a kind of regime-switching model, where default rates are either close to zero in "good" economic times or range from 5% to 10% in "bad" economic times (Figure 2, panel D).

Any such statistical modeling can be subject to a number of rational errors. Our hypothetical mortgage analyst could formulate a forecast using unreliable data. The particular forecast element of interest, such as mortgage default rates, may be dynamic and changing over time (i.e., have a nonstationary distribution), and the analyst may fail to consider this. In the spirit of "black swans," the estimate of the central tendency may be appropriate, but the mortgage analyst may fail to model extreme outcomes because they are so rare.

Besides these known rational errors, our hypothetical analyst could also develop a forecast relying on a type of psychological bias known as the representativeness heuristic. The representativeness heuristic, broadly, is a tendency to make errors in statistical inference. In particular, representativeness is a tendency to misattribute to a sample the characteristics of the population from which it is drawn; it is also a related tendency to misunderstand randomness.[4]

The summer carnival game. One way to understand the representativeness heuristic is to imagine the kind of random-draw game that might be found at a summer carnival.[5] A carnival hawker is calling on members of the public to play a game of chance. In front of the hawker is a large clear plastic container, filled with hundreds of red and black balls (Figure 3).

Figure 2. Statistical forecasts



Source: Vanguard, 2011.

3 The 5% default rate used in this paper is for illustration only and is purely hypothetical. It is not meant to represent the historical or expected default rates on mortgage-backed securities.

4 See Kahneman and Tversky, 1972.

5 This example is derived from an example (on an unrelated topic) presented by William Sharpe to a group of Vanguard institutional investors in New York in 2006.

In the game, players draw a few of the balls and guess at the proportion of red balls in the container. The player with the answer closest to the true proportion wins the game.

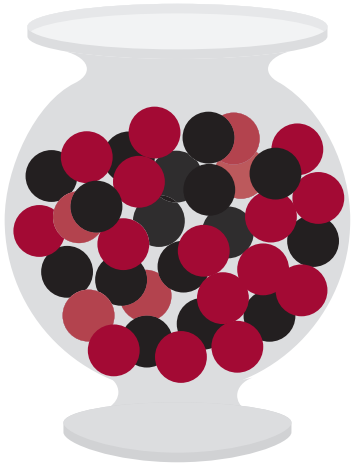
Player A goes first, and draws 20 balls (Figure 4, top panel). From his sample, he infers that 60% of the balls in the container are red. Player B enters the game, and being impatient, selects only 5 balls. Four of the five drawn are red, and so he concludes that 80% of the balls in the plastic urn are red (Figure 4, bottom panel).

From a statistical point of view, it is clear that Player A has the stronger claim to his estimate based on the larger sample size. The law of large numbers suggests that observers should believe that Player A's 60%, based on a larger sample, is the more accurate (assuming Player A chose the balls at random).

But surprisingly, in a wide array of settings, many observers tend to believe that Player B's estimate is more accurate—that 80% of the balls are red. Why? The simple explanation is that Player B simply has drawn more red and so appears less random. Of course, in any random draw there is some positive probability that a player could choose four red balls and a black. However, our mind tends to discount such outcomes and prefers a naïve view of randomness, such as a sequence of alternating red and black balls. So Player B is the person we most believe in because of the strength of his apparently nonrandom outcome. He has what we call a "hot streak" in sports or a "hot hand" in cards—winning four of five games, as it were.[6]

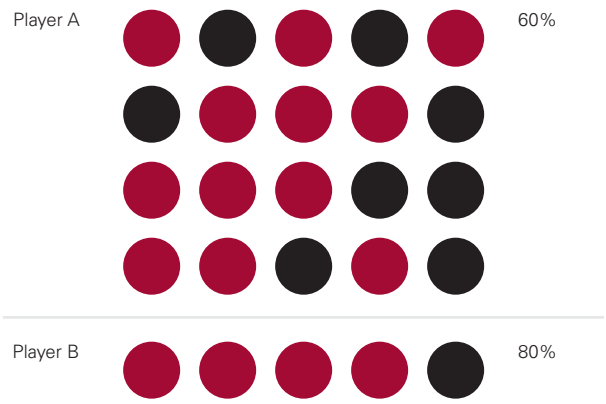
Figure 3. The carnival game

The question: What proportion of the container's balls are red?



Source: Vanguard, 2011.

Figure 4. Results from two players



Source: Vanguard, 2011.

Applying the representativeness heuristic to the mortgage problem is straightforward. Consider again a mortgage analyst estimating default rates on mortgage securities. By analogy, the container is the housing market and mortgage finance system. Player A is the long-term track record of prime mortgages. Player B is the recent short-term track record of subprime or exotic (such as interest-only or negative amortizing) mortgages. The mortgage analyst tends to assign to the subprime and exotic mortgages some of the general characteristics of prime mortgages, which dominate the container. In addition, the analyst overlooks the fact that the sample size of subprime and exotic mortgages is consistently smaller and so may not have the statistical validity of a larger, longer-term series.

Stage 2: Overconfidence

Representativeness errors arise because of an inability to think clearly about statistical relationships. But in Stage 2 of our model of bubbles, a second set of biases becomes pervasive—the tendency for forecasts of the future to lead to overconfidence, and, in particular, the tendency for market participants to extrapolate recent positive news into the future. These are the intertwined biases of overconfidence

6 This is sometimes known as having a belief in the "law of small numbers" (Tversky and Kahneman, 1971).

Representativeness and manager selection

The representativeness heuristic could play role in other financial decision-making errors. For example, consider the question of evaluating the past performance of money managers. Imagine that the results from the two carnival players (Figure 4) represent the track records of two money managers, Managers A and B. "Red" represents the fact that a given manager has surpassed his or her market benchmark.

From the example, Manager A, a seasoned portfolio manager, has 20 years of experience and a track record of outpacing the market index 60% of the time. Manager B, a newcomer, has five years experience but has a strong "hot streak" and has outpaced the market 80% of the time.

Our statistical or rational self tells us that Manager A is a better choice based on persistence of skill over time. But our human self tells us that Manager B is the better money manager because he has "won" more times, even though he has a much shorter track record. Statistically, it is easy to see that Manager B's track record could be the result of random chance. Psychologically, however, a "streak" of four good years does not fit our intuitive view of randomness, which should demonstrate itself with alternating good and bad years.

The representativeness heuristic may be one explanation for why investors chase performance in money manager selection.

and excessive extrapolation. In effect, in this stage of bubble formation, the forecasts of market participants become too rosy.

Overconfidence is perhaps the best-known bias in behavioral finance. It is found in a wide range of human decisions, financial and nonfinancial. On a number of dimensions, most individuals tend to rate themselves as above-average. For example, most drivers, joke tellers, and students rate themselves as better than average. The tendency to view oneself as above-average extends to professionals, including CEOs, managers in general, doctors, negotiators, investment bankers, and entrepreneurs. Overconfidence has been linked at the margin to gender. Men, on average, appear to be more overconfident. For example, they trade more in brokerage accounts—and generate inferior results—compared with women, who are more likely to be buy-and-hold investors.[7]

Overconfidence appears related to an overestimation or miscalibration of a decision-maker's own skills. Individuals who report that they are "100% sure" of a particular fact are usually wrong 20% of the time. Another reason may be an illusion of control. For example, players in one video-game study reported they were partially in control of the game, even though the controls were being operated solely by the machine and the players were exercising no control.

Related to overconfidence is a bias in decision-making known as excessive extrapolation. Excessive extrapolation is the tendency to overweight recent positive results and underweight long-term information. For example, flows to mutual funds are known to follow or "chase" recent past performance. And investors in 401(k) plans who are offered company stock are more likely to invest in it when the stock is doing well. Formal models of decision-making are being developed that incorporate this tendency to bias our forecast of the future based on recent positive experience.[8]

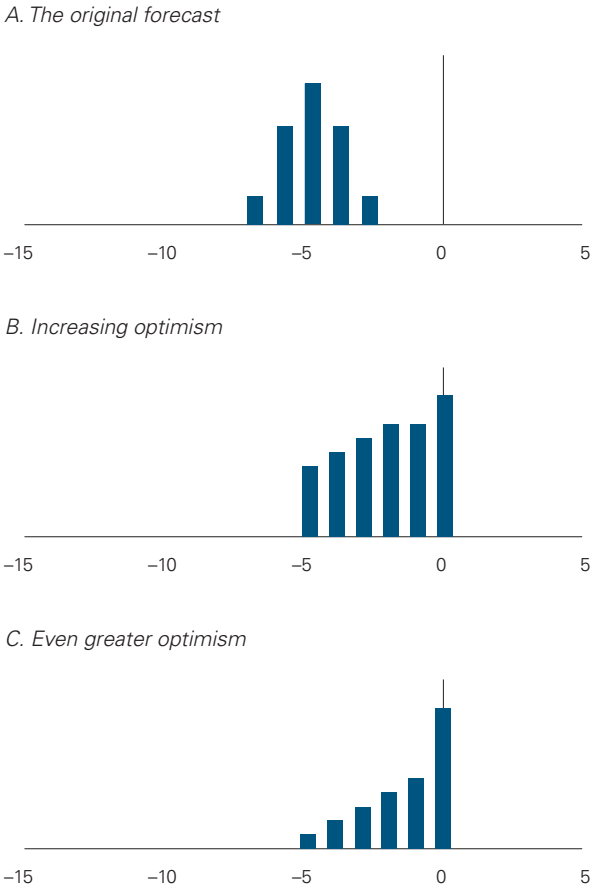
In Stage 2 of our model of bubbles, the combination of overconfidence and excessive extrapolation contributes to even more rosy forecasts of the future among agents in the financial system. Our mortgage analyst may start with a forecast default rate on mortgages modeled by a normal distribution with an expected value of 5% (Figure 5, panel A). Based on recent mortgage data showing below-average default rates, the forecast begins to shift to the right, with now 5% the maximum expected default rate (Figure 5, panel B). With additional short-term positive information, the forecast becomes centered on a 0% default rate, with only a low probability of any modest level of defaults (Figure 5, panel C). It is through such a dynamic that forecasts of future asset values—whether mortgages or internet stocks or other financial instruments—become increasingly skewed to the positive.

7 For summaries of research on overconfidence, see Nofsinger, 2011, chapter 2; and Zweig, 2007, chapter 5.

8 Fuster, Laibson, and Mendel, 2010, offer a recent assessment of the issue.

Separately, this phenomenon may be linked not simply to extreme fluctuations like bubbles and crashes, but also to more common fluctuations such as bull and bear markets. After a bear market in stocks, investors are keenly aware of stock market risk. Their experience, in other words, is well-calibrated with the actual risks of stocks. As economic conditions improve and stock prices rise, investors focus on recent positive experience and are tempted to forecast future returns that are skewed positively based on that experience. Eventually, the memory of negative returns recedes and loses some of its salience; as a result, forecasts of future returns become unrealistically positive. In such a way, the psychological response to return sequences can increase price fluctuations in a market.

Figure 5. Overconfidence in forecasts



Source: Vanguard, 2011.

Stage 3: Group transmission/amplification

In any financial system, at any given point in time, there are always agents with different views of the future—some positive and some negative, some very rosy and some very gloomy. The differences among these competing views are reconciled in the daily price negotiations that occur in the financial markets. In such a world, extreme and unrealistic views such as overconfidence or excessive pessimism are competed away. More experienced investors profit from the mistakes of investors with poorly calibrated views.

How, then, does an entire financial system or market become overconfident? How can an individual's forecasting bias toward excessive extrapolation be transformed into group- or systemwide behavior? One of the necessary conditions of a bubble is a surge in enthusiasm for a given asset among a substantial majority of market participants. Although contrarians may seek to take the other side of the trade, and bet on falling prices for the asset, they are, by definition, too few in number to provide a countervailing force. As a result, the price of the asset soars upward.

In Stage 3 of our model of bubbles, two characteristics of group psychology—groupthink and group polarization—come into play. It is through such dimensions that individual decision-making biases are transmitted and amplified to a group level, where that group is a financial market or system as a whole.[9]

Groupthink is a form of poor decision-making usually associated with fiascos. When under the influence of groupthink, a particular group begins to feel invulnerable; it rationalizes its behavior; and it systematically ignores external and contradictory sources of information. Groupthink is also characterized by a failure to examine alternatives, poor information search, and a failure to work out contingency plans. Late-stage asset price bubbles would seem to have many of these characteristics.

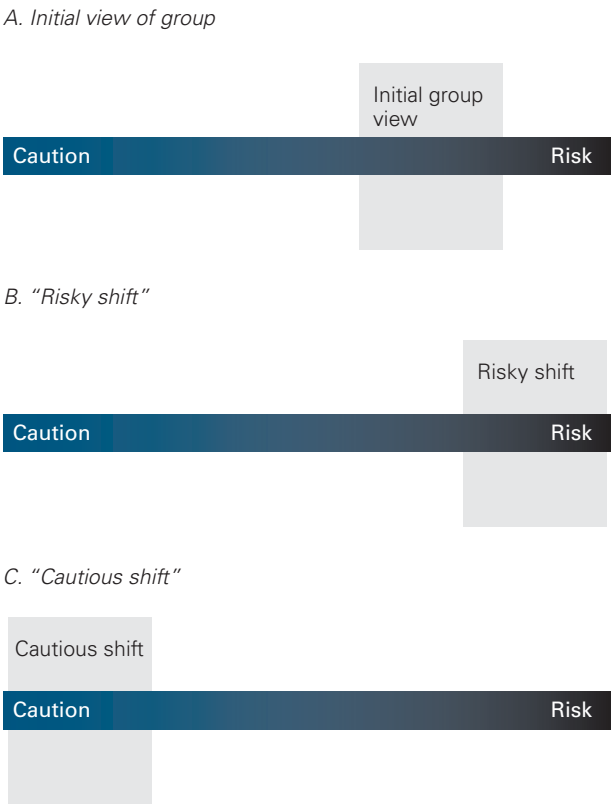
Group polarization is the tendency for a group to make riskier decisions than individuals alone would make. Suppose for a given decision, the initial view of a group of decision-makers—say a project team, an investment committee, or a political group like a city council—is inclined to some measured amount

9 For a summary of these group characteristics and their application to decisions by investment committees, see Mottola and Utkus, 2009.

of risk-taking (Figure 6, panel A). As a group, they can sometimes move toward an even riskier decision than the sum of the individuals' own beliefs, a phenomenon known as a "risky shift" (Figure 6, panel B). The result is an experience that occasionally arises with teamwork —a group makes a decision, but as individuals walk out of the room, they speak separately to one another and realize that most of them view the team decision as too risky.

Although these two terms usually refer to small groups —for example, project or work teams or a leadership team—modern communication technology allows a "group" to include an entire market or financial system. Bubbles do not form merely because particular individuals are making representativeness or overconfidence errors. In a competitive marketplace, such views, if flawed, would eventually lead to monetary losses. Bubbles arise when the technology of communications contributes not just to exchange of information among individuals, but to a collective shift to riskier behavior in the system as a whole. Through the process of our social interactions in the marketplace, the entire financial system shifts to an even higher risk level as a result—and to a level that many market participants would individually agree is too risky.

Figure 6. Group polarization



Source: Vanguard, 2011.

There is little formal research that attempts to link these social-psychological elements to bubble formation, although recent finance research on peer effects does document the importance of social interactions in influencing savings and portfolio behavior. From a historic perspective, the financier Bernard Baruch attempted to capture this dynamic of group psychology in his analysis of the U.S. stock market crash of 1929. (His observations also incorporate an element of evolutionary biology.)

> "Have you ever seen in some wood, on a sunny quiet day, a cloud of flying midges—thousands of them—hovering, apparently motionless, in a sunbeam? . . . Yes? . . .
>
> Well, did you ever see the whole flight—each mite apparently preserving its distance from the others—suddenly move, say three feet, to one side or the other?
>
> *Well, what made them do that?*
> A breeze? I said a *quiet day*. But try to recall—did you ever see them move directly back again in the same unison? Well, what made them do *that*? Great human mass movements are slower of inception but much more effective."[10]

By analogy, a financial system, as a group of human decision-makers, may be shifting to even riskier positions collectively, just as the cloud of midges are shifting on a summer's day. But because group members preserve their relative distance from each other, their internal view of the market and the role of market participants is unchanged—it does not appear that the group's risk position has changed, even though it has.

In other contexts, group polarization and groupthink are sometimes referred to as herding (another evolutionary biological term).[11] The important element, in terms of its influence on bubble formation, is that it leads to the transformation of individual biases into group or social biases. In particular, it leads to a financial or social system taking more risk than it otherwise might because of the very dynamics of communicating and acting

10 See the foreword by Andrew Tobias in Mackay, 1841, 1980.
11 Grinblatt, Titman, and Wermers, 1995.

as group members that are facilitated by modern technology. Instead of moderating excessively optimistic forecasts by providing a mechanism for competing views to form, the technology amplifies decision-making errors across the system and among market participants, and accelerates representativeness and overconfidence errors.

Stage 4: Recalibration

Stage 4 of a market bubble is the recalibration of expectations with reality and the concurrent crash. This is the point at which actual data from the field causes market participants to begin to question their too-rosy forecasts and the consensus group opinion. In particular, it consists of a recalibration of the overly optimistic group forecasts based on the actual observed data in the economy and financial markets.

At some point, observed data becomes so overwhelming as to call into question the excessively optimistic forecasts of market participants. In the case of bubbles in stock prices, this occurs at the point where expected revenue and earnings growth rates fall somewhat short of optimistic expectations. In the case of a mortgage bubble, it occurs when default rates begin to rise unexpectedly, at odds with the original assumptions of decision-makers in the markets.

At one level, the recalibration phase is the reassertion of more rationally grounded expectations for the future. Market participants come to recognize that their forecasts of the future were unduly positive and revise their expectations accordingly. Depending on how overly optimistic the assumptions had become, the size of this change could be substantial.

Yet this rational reassessment can also be amplified by the same group polarization process that caused the bubble to inflate—this time working in reverse. In this stage, the group dynamic is known as a "conservative shift," the opposite of a risky shift (Figure 6, panel C). The collective group behavior becomes even more risk-averse than the individual participants believe is realistic. In keeping with this shift in group psychology, it is not the case that market participants simply modify their views at the margin. Such an adjustment would mean a gradual and orderly deflating of an asset price bubble. Instead, consistent with a group polarization effect, a large group of individuals in the system suddenly changes its mind and shifts sharply to an overly cautious outlook for the asset in question.

Continuing our analogy, suppose the new evidence points to the fact that default rates on certain mortgages are not going to be 5%, but instead 25%. The effect of group polarization would be for market participants to adopt the view that the expected default rate is now 40%, not 25% as suggested by the data. The collective estimate, as a result, becomes even more cautious than the actual data suggests. The group process at the financial system level only accelerates or amplifies the move to a more extreme, in this case conservative, opinion.

Implications

According to the model outlined in this paper, market participants, both as individuals and as a group, can occasionally make forecasts of the future that are subject to psychological biases. The result leads to wide swings in prices—so-called market bubbles and crashes. The model includes: (1) initial errors in statistical inference caused by the representativeness heuristic; (2) the emergence of skewed forecasts because of overconfidence and excessive extrapolation; (3) the amplification of these views through a "risky shift" or group polarization process across the financial system; and, finally, (4) the resetting of forecasts to an excessively cautious view.

One implication of this model is that the growth of bubbles is both an individual and a group phenomenon. In a standard model of rational decision-makers, expansion in the technology and sophistication of financial systems would improve the price discovery process in markets and investor understanding of intrinsic asset values. In our proposed model, these same systems can be used to transmit erroneous forecasts among market participants and lead to a systemwide amplification of decision-making errors.

A second implication of the model is that bubble behavior is, at its origins, a psychological phenomenon, and thus may be less amenable to remedial education than, say, mistakes in fact or gaps in information. For example, a household that does not invest in the stock market because of a lack of information about equity investing may be persuaded to invest in stocks through an investor literacy campaign. However, it is not as obvious how to teach investors to mitigate a bias toward overconfidence or toward representativeness errors.

So how might investors seek to understand bubbles, avoid participating in them, and, ultimately, avoid their damaging effects? One strategy is to devote

more energy to gaining knowledge and experience—not only knowledge of the history of bubbles, but also of a better understanding of statistics. Learning to think more clearly about statistics, or developing rules of thumb to counteract decision biases like excessive extrapolation, could be useful. For example, one common rule of thumb is for investors to be skeptical in the face of information that is too good to be true. It could be that such "good" rules of thumb could be helpful in counteracting "bad" behavioral biases.

There is some evidence from finance experiments done in laboratories that inexperience plays an important role in the prevalence of bubbles and crashes. Inexperienced investors seem more prone to miscalculation, and so price fluctuations are initially quite large in this group. As they gain experience, the tendency toward bubble behavior, at least in the hypothetical laboratory setting, dissipates. These findings, at least indirectly, support the notion of investor education and literacy as important elements to mitigate bubble tendencies.[12]

A second strategy focuses on the management of emotions. An emerging framework for thinking about decision-making is to divide decisions into those governed by deliberate processes and those governed by automatic processes. The former are slow, calculating, conceptual, and involve the manipulation of symbols like language and numbers. The second are rapid, intuitive, visceral or emotional, and often based on nonverbal or nonnumeric reasoning. Automatic processes may be more easily dominated by emotional or psychological biases and lead to decision-making errors. One recent experiment suggested that emotions tended to impede effective investment choices and that it might be better if investors were more cool and calculating and less emotional.[13]

A third strategy from behavioral finance is to "widen the frame"—to focus attention on the broadest frame of reference for decision-making. In the case of investors, this means focusing on the aggregate performance of a portfolio over time and the growth of its value relative to long-term objectives, not on near-term fluctuations or on the behavior of individual holdings—including rapidly escalating prices in a given asset class. In studies of loss aversion (the tendency to overreact emotionally to losses), investors were much more sensitive to losses when focused on short-term performance or on the behavior of individual investments. When portfolio risk levels are viewed at the aggregate level and over time, emotional sensitivity to losses appears to decline. In some ways, "widening the frame" may appeal to the cognitive or rational decision processes and less to the automatic, emotional ones.

A fourth strategy from research in group psychology suggests that introducing external information or viewpoints to a decision can improve outcomes. Since we know that individuals may have a difficult time calibrating their own views, the idea is to use independent external data to provide independent calibration. For example, individual investors or investment committees might deliberately go out of their way to seek third-party sources of information, opinion, and insight.

In this capacity, an advisor or investment consultant can play an important role as an independent source of information for individual investors or committees. At the same time, advisors and consultants can also be subject to the same decision-making biases as their clients. They run the risk of simply confirming their clients' biases in order to be accommodating to their clients' needs or their own business objectives. The challenge for advisors and consultants is to work against these tendencies and serve as a source of independent, external insight.

Our understanding of how psychological elements influence decision-making is relatively new. How those factors might influence the formation of market bubbles is even more uncertain. As a result, the model sketched out in this paper should be viewed as preliminary. And in an important way, the model is speculative, as it is not feasible to carry out controlled real-world experiments on market bubbles. Nonetheless, it is likely that some of the elements highlighted in the model will play a role in developing a deeper understanding of market bubbles in the future.

12 Smith et. al., 1988, demonstrated the impact of inexperienced traders on the formation of bubbles, and Van Boening, et. al., 1993, demonstrated an even stronger link between inexperience and bubble/crash market behavior. However, Dufwenberg et. al., 2005, provides an alternative view.

13 In the experiment, a group of participants played an investment game. Some suffered from brain lesions, impeding their ability to process emotions, while others did not. As the investment game ensued, participants with ordinary emotions invariably dropped out of the game early, while participants with the brain lesions were more likely to remain in the game and play it optimally. This study confirmed that emotions impeded optimal behavior, at least in a laboratory setting. See Shiv, Loewenstein, Bechara, Damasio, and Damasio, 2005.

References

Campbell, John Y. and Robert J. Shiller. 2005. "Valuation Ratios and the Long-Run Stock Market Outlook: An Update." In *Advances in Behavioral Finance, Volume II*, Richard H. Thaler, ed. Princeton University Press, Princeton, NJ. 173-201.

Chancellor, Edward. 2000. *Devil Take the Hindmost: A History of Financial Speculation*. Plume. Penguin Putnam, Inc., New York, NY.

Dufwenberg, Martin, Tobias Lindqvist, and Evan Moore. 2005. "Bubbles and Experience: An Experiment." *American Economic Review*. 95(5). 1731-1737.

Fuster Andreas, David Laibson, and Brock Mendel. 2010. "Natural Expectations and Macroeconomic Fluctuations." *The Journal of Economic Perspectives*. 24(4). 67-84.

Grinblatt, Mark, Sheridan Titman, and Russ Wermers. 1995. "Momentum Investment Strategies, Portfolio Performance and Herding: A Study of Mutual Fund Behavior." *American Economic Review*. 85(5). 1088-1105.

Kahneman, Daniel and Amos Tversky. 1972. "Subjective probability: A judgment of representativeness." In *Judgment under uncertainty: Heuristics and biases*, Daniel Kahneman, Paul Slovic, and Amos Tversky, eds. Cambridge University Press, Cambridge, UK. 1982. 32-47.

Kindleberger, Charles P. and Robert Aliber. 2005. *Manias, Panics and Crashes*. John Wiley and Sons, Inc., Hoboken, NJ.

Mackay, Charles. 1841, 1980. *Extraordinary Popular Delusions and the Madness of Crowds*. Harmony Books, New York, NY. 1980 foreword by Andrew Tobias.

Mottola, Gary R. and Stephen P. Utkus. 2009. *Group decision-making: Implications for investment committees*. Vanguard Investment Counseling and Research. institutional.vanguard.com

Nofsinger, John R. 2011. *The Psychology of Investing*. Pearson Education, Boston, MA.

Shiv, Baba, George Loewenstein, Antoine Bechara, Hanna Damasio, and Antonio R. Damasio. 2005. "Investment behavior and the negative side of emotion." *Psychological Science*. 16:435-439.

Smith, Vernon L., Gerry L. Suchanek, and Arlington W. Williams. 1988. "Bubbles, Crashes and Endogenous Expectations in Experimental Spot Asset Markets." *Econometrica*. 56(5). 1119-51.

Tversky, Amos and Daniel Kahneman. 1971. "Belief in the law of small numbers." In *Judgment under uncertainty: Heuristics and biases*, Daniel Kahneman, Paul Slovic, and Amos Tversky, eds. Cambridge University Press, Cambridge, UK. 1982. 23-31.

Van Boening, Mark V., Arlington W. Williams, and Shawn LaMaster. 1993. "Price bubbles and crashes in experimental call markets." *Economics Letters*. 41(2). 179-185.

Zweig, Jason. 2007. *Your Money and Your Brain*. Simon and Schuster, New York, NY.

P.O. Box 2900
Valley Forge, PA 19482-2900

Connect with Vanguard® > vanguard.com
> global.vanguard.com (non-U.S. investors)

Vanguard research >
Vanguard Center for Retirement Research
Vanguard Investment Counseling & Research
Vanguard Investment Strategy Group

E-mail > research@vanguard.com

All investing is subject to risk. Investments in bond funds are subject to interest rate, credit, and inflation risk. Diversification does not ensure a profit or protect against a loss in a declining market.

CRRMBP 022011