April 1, 2012

Self-Enhancing Transmission Bias and Active Investing

Bing Han[1] David Hirshleifer[1]

Individual investors often invest actively and lose thereby. Social interaction seems to exacerbate this tendency. In the model here, senders' propensity to discuss their strategies' returns, and receivers' propensity to be converted, are increasing in sender return. The rate of conversion of investors to active investing is convex in sender return. Unconditionally, active strategies (high variance, skewness, and personal involvement) dominate the population unless the mean return penalty to active investing is too large. Thus, the model can explain overvaluation of 'active' asset characteristics even when investors have no inherent preference over them.

[1]Bing Han is from McCombs School of Business, University of Texas at Austin, and David Hirshleifer is from Merage School of Business, University of California at Irvine. We thank workshop participants at the Goizueta School of Business at Emory University, Nanyang Business School at Nanyang Technical University, the Stern School of Business at New York University, the Rady School of Business at UCSD, the Anderson Graduate School of Management at UCLA, the Kenan-Flagler Business School at the University of North Carolina, the Economics Department of Cambridge University, the Said School of Business at Oxford University, and the Institute for Mathematical Behavioral Sciences at UC Irvine; participants at the National Bureau of Economic Research behavioral finance working group meeting in Chicago, the American Finance Association annual meetings in Denver, CO, the Applied Behavioral Finance Conference at UCLA, and the 2011 Linde Conference at Caltech; the NBER discussant, Nick Barberis; the AFA discussant, Blake LeBaron; the ABF discussant, Andrea Eisfeldt; Jean-Paul Carvalho, David Dicks, Nikolai Roussanov, Siew Hong Teoh, Paul Tetlock, Rossen Valkanov, Michela Verardo, Ivo Welch, Jeff Wurgler, and Wei Xiong for very helpful comments; and Jason Chan, SuJung Choi, Major Coleman, and Josh Levin for helpful research assistance.

1 Introduction

A neglected topic in financial economics is how investment ideas are transmitted from person to person. In most investments models, the influence of individual choices on others is mediated by price or by quantities traded in impersonal markets. However, more direct forms of social interaction are also important for investment decisions. As Shiller (1989) put it, "...Investing in speculative assets is a social activity. Investors spend a substantial part of their leisure time discussing investments, reading about investments, or gossiping about others' successes or failures in investing." In one survey, individual investors were asked what first drew their attention to the firm whose stock they had most recently bought. Almost all named sources which involved direct personal contact; personal interaction was also important for institutional investors (Shiller and Pound 1989). Shiller (1990, 2000b) discusses other indications that conversation matters for security investment decisions and bubbles. Furthermore, a recent empirical literature documents social interactions in investment decisions by individuals and money managers, including selection of individual stocks.[2]

Our purpose here is to model how the *process by which ideas are transmitted* affects social outcomes, with an application to active versus passive investment behavior. We view the transmission process here as including both in-person and electronic means of conversation, as well as one-to-many forms of communication such as blogging and news media. Our approach is based on the idea that conversational biases can favor superficially-appealing but mistaken ideas about personal investing (Shiller (2000a, 2000b)).

A key puzzle about individual trading is that individual investors trade actively and on average lose money by doing so relative to a passive strategy such as holding the market (Barber and Odean (2000b), Barber et al. (2009)). Calvet, Campbell, and Sodini (2007) report that idiosyncratic risk exposure of Swedish households accounts for half of the return variance for the median household. Even when delegating investment decisions, investors favor actively managed mutual funds over index funds (despite the aggregate underperformance of actively managed funds relative to index funds net of costs).[3] In addition to net underperformance relative to benchmarks, investing in active funds adds idiosyncratic

[2]See, e.g., Kelly and O'Grada (2000), Duflo and Saez (2002, 2003), Cohen, Frazzini and Malloy(2008, 2010), Ivkovich and Weisbenner (2007), Brown et al. (2008), Hong, Kubik, and Stein (2004, 2005), Massa and Simonov (2005), Shive (2010), and Gray (2009).

[3]Carhart (1997) and Daniel, Grinblatt, Titman, and Wermers (1997) find that active funds do not tend to outperform against passive benchmarks. French (2008) documents very large fees paid in the aggregate by investors to active funds.

portfolio volatility associated with deviations from the benchmark portfolio. These choices may reflect sheer ignorance, but often reflect a belief by individual investors that they can identify managers who will outperform the market. Financial scams such as the Madoff scheme also rely on investors' belief that they can identify superior investment managers.

A plausible explanation for excessive investor trading is overconfidence (DeBondt and Thaler (1995), Barber and Odean (2000b)), a basic feature of individual psychology. However, trading aggressiveness seems to be greatly exacerbated by social interactions. For example, more than other investors, participants in investment clubs seem to select individual stocks based on reasons that are easily exchanged with others (Barber, Heath, and Odean (2003)); select small, high-beta, growth stocks; turn over their portfolios very frequently; and underperform the market (Barber and Odean (2000a)). Contagion in stock picking by individuals and institutions is contagion in a type of speculative behavior. There is also evidence that self-reported stock market participation increases with measures of social connectedness (Hong, Kubik, and Stein (2004)).[4]

These considerations suggest looking beyond direct individual-level psychological biases alone, to an explanation that emerges from the process of social interaction. The sheer fact of behavioral contagion, as analyzed and documented in a body of theory and empirical work, does not in itself explain a tilt toward active trading, since either active and passive strategies can spread from person to person. So bias in the transmission process is an essential ingredient for addressing this issue.

The explanation we propose here is that investors like to recount to others their investment victories more than their defeats, and that listeners do not fully discount for this. We call this behavior *self-enhancing transmission bias*, or *SET*.

Both a rational concern for reputation and psychological bias can contribute to SET. Talking preferentially about one's successes can be a means for an individual to improve his personal reputation. A literature from psychology and sociology on self-presentation and impression management indicates that people seek to report positively about themselves,

[4]During the millennial high-tech boom, investors who switched early to online trading subsequently began to trade more actively and speculatively, and earned reduced trading profits (Barber and Odean (2002)). It seems likely that the greater inclination or opportunity of such investors to use the internet was associated with greater access to or use of online forms of social interaction, such as e-mail and investment chat rooms. Chat rooms were, at least in popular reports, important in stimulating day trading. Furthermore, there is evidence that impersonal social interactions, such as those between media commentators and viewers, affect trading and prices (after controlling for fundamentals). For example, there is evidence that media coverage of individual stocks affects individual trading (Parsons and Engelberg (2009)), stock prices (Tetlock (2007), Engelberg, Sasseville, and Williams (2009)) and the cross-section of stock returns (Fang and Peress (2009)).

as constrained by the need to be plausible and to satisfy presentational norms (Goffman (1961), Schlenker (1980)). In a review of the impression management field, Leary and Kowalski (1990) discuss how people tend to avoid lying, but selectively omit information, so that "Impression management often involves an attempt to put the best parts of oneself into public view" (pp. 40-1). Similarly, Leary ((1996) pp. 4, 121) discusses tactics of selective information presentation such as concealing discreditable information. Consistent with SET, a literature (summarized in the review of East, Hammond, and Wright (2007)) finds that positive word-of-mouth discussion tends to predominate over negative discussion for a wide set of products. Wojnicki and Godes (2010) offer as explanation that consumers disproportionately discuss their successful product experiences in order to persuade others that they are expert at product choice.

Furthermore, there is evidence from psychology research of self-enhancing thought processes, such as the tendency of people to attribute successes to their own qualities and failures to external circumstances or luck (Bem (1972), Langer and Roth (1975)).[5] Self-enhancing psychological processes encourage people to think more about their successes than their failures (see, e.g., the model Benabou and Tirole (2002)). It is a small step from thinking in a self-enhancing way to talking in such a way.

In the model, members of a population of investors adopt either an Active (A) or Passive (P) investment strategy. A is the riskier, less conventional, more affect-triggering, or more cognition- or effort-intensive option. SET creates an upward selection bias in the reports received by other investors about the profitability of the chosen strategy: they hear about good outcomes more than bad outcomes. The size of the selection bias increases with return variance; for example, if variance is zero the selection bias vanishes. So if A has higher variance than P and if listeners do not fully discount for the biased sample they observe, they will overestimate the value of adopting A relative to P. Furthermore, if receivers attend more to extreme outcomes, high skewness strategies will tend to spread, because such strategies more often generate the extreme high returns which are most often reported, attended to, and influential. As a result, A spreads through the population unless it has a sufficiently strong offsetting disadvantage (lower expected return).

[5]The 'totalitarian ego' describes the tendency in many contexts for people to filter and interpret information to the greater glory of the self (Greenwald (1980)). People differentially recall information in ways favorable to their self-esteem (see, e.g., Section 5.3 of von Hippel and Trivers (2011)). Motivated reasoning (Kunda (1990)), the tendency to draw inferences based on desired conclusions (e.g., that the individual possesses desirable qualities) rather than on the merits, can support self-enhancement. There is evidence of self-enhancing behaviors in investing; Karlsson, Loewenstein, and Seppi (2009) find that Scandinavian investors reexamine their portfolios more frequently when the market has risen than when it has declined.

The analysis offers a possible explanation for a range of patterns in trading and returns, including the participation of individuals in lotteries with negative expected return; the preference of some investors for high variance or high skewness ('lottery') stocks; overvaluation of growth firms, distressed firms, firms that have recently undertaken Initial Public Offerings (IPOs), and high idiosyncratic volatility firms; heavy trading and overvaluation of firms that are attractive as topics of conversation (such as sports, entertainment, and media firms, firms with hot consumer products, and local firms); and the association of these effects, and the extent of stock market trading in general, with proxies for social interactiveness. The approach also offers new empirical implications.

A general theoretical literature on social interaction in economics focuses on its effects on the efficiency of information flows, and on behavioral convergence (herding).[6] There has also been theoretical analysis of the effects of social interactions in fields such as anthropology (Henrich and Boyd (1998)), zoology (Lachlan, Crooks, and Laland (1998), Dodds and Watts (2005)), and social psychology (Cialdini and Goldstein (2004)). Finance models have examined how social interactions affect information aggregation, and potentially can generate financial crises.[7] This paper differs from this literature in examining how SET affects the evolutionary outcome. Economists have also modelled how cultural evolutionary processes affect ethnic and religious traits, and altruistic preferences (Bisin and Verdier (2000, 2001)). The focus here is on understanding investment and risk-taking behavior.

2 The Model

2.1 Social Interactions, Timing of Events, and Population Shifts

The Population

We consider a population of n individuals who adopt one of two types of investment strategies, A (Active) and P (Passive), which have different return probability distributions

[6] Scharfstein and Stein (1990) model herd behavior as a reputational phenomenon. Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992) study rational learning by observing the actions of others; Ellison and Fudenberg (1995, 1995) study rules of thumb and social learning by observation of actions and signals. Morris (2000) models strategy contagion in game-theoretic interactions. Banerjee and Fudenberg (2004) analyze social learning in a rational setting. DeMarzo, Vayanos, and Zwiebel (2003) model how 'persuasion bias' affects beliefs when information spreads through a social network. Jackson (2008) reviews the theory of social interaction in networks.

[7] DeMarzo, Vayanos, and Zwiebel (2001) model how information flows in social networks affect asset markets; Cipriani and Guarino (2002, 2008) model financial crises and herd behavior. Welch (1992) models social interactions in investment. Devenow and Welch (1996), Brunnermeier (2001), and Hirshleifer and Teoh (2003, 2009) review the theory of herding in financial markets. Ozsoylev and Walden (2011) provides a rational model of information and asset pricing when investors communicate within a social network.

(to be specified later in Section 2.6). In each period (generation), θn pairs of individuals are randomly selected to meet, where $0 < \theta \leq 1/2$ is a parameter describing the intensity of social interactions. The larger the θ, the more sociable is the population. For each pair, one randomly becomes the sender and the other the receiver.[8] The returns of the sender and receiver from their current strategies over the period are realized. The sender either does or does not report his return to the receiver, where the probability of doing so, denoted $s(R_i)$, is increasing in the sender's return. Finally, a receiver who receives a message from the sender either is or is not transformed into the type of the sender, where the probability of this occuring, denoted $r(R_i)$, is also increasing in the sender's return.

Let n_i be the number of type i in the current period or generation and n_i' be the number in the next generation, and let

$$\begin{aligned} f_i &\equiv \frac{n_i}{n} \\ f_i' &\equiv \frac{n_i'}{n}, \quad i = A, P, \end{aligned} \tag{1}$$

where $f_A + f_P = f_A' + f_P' = 1$. In the rest of the paper, we use $f \equiv f_A$ to denote the population frequency of type A individuals. Note that n, the total number of individuals in population, does not change across generations[9], while the fraction of individuals adopting type A or type P change over time influenced by social interactions.

In AA or PP pairs, there is no change in the frequency of individuals adopting each strategy. When A and P meet, with probability s the sender communicates his performance and upon receiving the message, the receiver converts to the type of the sender with probability r. We assume that the value of the sending and receiving functions (s and r) depend only on the sender's return. For given return, they are independent of the sender's and receiver's types (i.e, whether the sender is A and the receiver P, or vice versa). Thus, the transformation of types after a meeting depends on who becomes the sender as well as the sender's return.

Let $T_{ij}(R_i)$ be the probability that the sender, who is of type $i = A, P$, transforms the receiver, who is of type j, into type i, where T_{ij} is a function of the sender's return R_i. The

[8] In actual conversations, often both parties recount their experiences. Our sharp distinction between being a sender and a receiver in a given conversation is stylized, but since we allow for the possibility that either type be the sender, is unlikely to be misleading.

[9] A standard model for allele (gene type) frequency change in evolutionary biology is the Moran process (Moran (1962)), in which in each generation exactly one individual is born and one dies, leaving population size constant. Here we apply a Moran process to the spread of a cultural trait or, in the terminology of Dawkins (1976), a 'meme'.

shifts in f, the frequency of type A individuals after one pair of individuals meet is

$$f' - f = \begin{cases} \frac{1}{n} & \text{with probability} \quad \left(\frac{\chi}{2}\right) T_{AP}(R_A) \\ -\frac{1}{n} & \text{with probability} \quad \left(\frac{\chi}{2}\right) T_{PA}(R_P) \\ 0 & \text{with probability} \quad 1 - \left(\frac{\chi}{2}\right) [T_{AP}(R_A) + T_{PA}(R_P)], \end{cases} \tag{2}$$

where χ is the probability that a cross-type pair is drawn,

$$\begin{aligned} \chi &\equiv \left(\frac{n_A}{n}\right)\left(\frac{n - n_A}{n-1}\right) + \left(\frac{n - n_A}{n}\right)\left(\frac{n_A}{n-1}\right) \\ &= \frac{2nf(1-f)}{(n-1)}, \end{aligned} \tag{3}$$

We model the transformation probability schedule as the result of conversational initiations and sendings of performance information by senders, and of the receptiveness of receivers. The next subsection considers senders, and the one that follows considers receivers.

2.2 Self-Enhancement and the Sending Function

Owing to self-enhancing transmission bias, we assume that the probability that the sender of type i sends is increasing in the performance of the sender's strategy, R_i, so $s'(R_i) > 0$.[10] A sender may, of course, exaggerate or simply fabricate a story of high return. But if senders do not always fabricate, the probability of sending will still depend upon the actual return. We apply a linear version of SET,

$$s(R_i) = \beta R_i + \gamma, \qquad \beta, \gamma > 0, \tag{4}$$

where i is the type of the sender. Since the sending function is type-independent, β and γ have no subscripts.

To ensure that $0 \leq s_i \leq 1$, we require that $-(\gamma/\beta) \leq R_i \leq (1-\gamma)(\beta)$. Under reasonable parameter values for β and γ, we can ensure that the probability of return falling outside this range is negligible.[11]

[10] SET is evident in Alexander Pope's remark in a letter to his stock broker during the South Sea bubble that "I daily hear such reports of advantages to be gaind by one project or other in the stocks, that my spirit is up with double zeal, in the desire of our trying to enrich ourselves. ...Let but Fortune favor us, & the World will be sure to admire our Prudence. If we fail, lets een keep the mishap to ourselves." (March 21, 1770); quoted in Chancellor (2000) ch. 2, p. 64. Potentially consistent with SET, Shiller (1990) provides survey evidence that people talked more about real estate in U.S. cities that have experienced rising real estate prices than those that have not.

[11] For example, corresponding to $\beta = 2$ and $\gamma = 0.4$, the interval that guarantees the sending probability

The assumption that sending is stochastic reflects the fact that raising a topic in a conversation depends on both social context and on what topics the conversation partner happens to raise. Strong performance encourages a sender to discuss his investments, but senders also prefer not to violate conversational norms. In some contexts even a reluctant sender with poor return will feel pressure to discuss his performance. In others an eager sender with high return may not get a chance to talk about it without seeming immodest.[12]

The positive slope β of the sending schedule reflects self-enhancing transmission. Consistent with $\beta > 0$, empirically, using a database from a Facebook-style social network for individual investors, **?**) report that the frequency with which an investor contacts other traders is increasing in the investor's short-term return.

SET creates a selection bias in the set of returns observed by receivers. In circumstances where the sender's self-esteem or reputation is more tightly bound to performance, SET should be stronger, and therefore β higher.[13,14] The constant γ reflects the 'conversability' of the investment choice. When the investment is an attractive topic for conversation the sender raises the topic more often. The sender also raises the topic more often when conversations are more extensive, as occurs when individuals are more sociable (how much they talk and share information with each other). So γ also reflects investor sociability. It would be plausible to further distinguish conversability of A versus P, where $\gamma_A > \gamma_P$. However, the model generates survival of A even without a conversability advantage.

2.3 The Receiving Function

For a mixed pair of individuals, consider now the likelihood of a receiver of type j being converted to the sender's type i. Given a sender return R_i and that this return is indeed sent, the conditional probability that the receiver is converted is denoted $r(R_i)$.

Messages sent by a sender with strong performance are more persuasive than messages

to between between 0 and 1 is the sender's return R is between -20% and 30%. The probability of returns that are more extreme returns than this over, e.g., one month is small. It would be possible, alternatively, to use a piecewise linear specification for the sending function (bottoming out at zero and topping out at one), but this would make the algebra unwieldy without obvious compensating insights.

[12]Reporting favorable information about one's achievements and competence often lead to negative reactions in onlookers when the information is not provided in response to a specific question (Holtgraves and Srull (1989)).

[13]This consideration suggests that β will be higher for individuals who pursue the active strategy than the passive strategy. However, for simplicity we assume that the sender function (including β) is independent of the type of the sender.

[14]An additional incentive for selection bias in performance reporting is present for firms that seek to market their strategies, as with fund families starting many funds and then continuing only those that have performed well.

from a sender with weak performance, so we assume that $r'(R_i) > 0$. This accommodates the possibility that receivers sometimes have a degree of skepticism about the selection bias in the messages they receive, as well as sender lying and exaggeration.[15]

Other things equal, discounting by receivers for the upward selection bias implies less optimistic inferences about the desirability of the sender's strategy. However, there is extensive evidence in various contexts that observers do not fully discount for selection biases in the data they observe, a phenomenon called selection neglect.[16] Selection neglect is to be expected if individuals with limited processing power automatically process data in intuitive ways, and do not always take the extra cognitive step of adjusting for selection bias.[17] It also follows from the abovementioned representativeness heuristic and its corollary, the law of small numbers. If individuals view their small samples as highly representative of the population, they will not adequately recognize the need to adjust for selection bias.

If a receiver does not understand that sending increases with strategy returns as implied by the sending function (4), and believes that past performance is indicative of strategy value, then the receiver draws credulous conclusions about the value of the sender's strategy. This tends to raise the receiving function, which promotes a frothy churning in beliefs from generation to generation.

There is evidence that investors do overweight past performance as an indicator of future performance. Despite the existence of some well-known return predictability anomalies, the

[15]For example, if the sender always exaggerates return upward by a fixed amount, the receiver may or may not be sophisticated enough to 'undo' this bias, but in either case there is a mapping summarized by the r function from the sender's return to the probability that the receiver converts.

[16]See, e.g., Nisbett and Borgida (1975), Ross, Amabile, and Steinmetz (1977), Nisbett and Ross (1980), and Brenner, Koehler, and Tversky (1996). People tend to place heavy weight on sample data even when they are told that it is atypical (Hamill, Wilson, and Nisbett (1980)), and often naively accept sample data at face value (Fiedler (2008)). Nisbett et al. (1983) find better adjustment for selection bias when individuals are cued with clear and specific information about the selection process. Koehler and Mercer (2009) find that mutual fund families advertise their better-performing funds, and find experimentally that both novice investors and financial professionals suffer from selection neglect. Auction bidders in economic experiments tend to suffer from a winner's curse (neglect of the selection bias inherent in winning), and hence tend to lose money on average (Parlour, Prasnikar, and Rajan (2007)). For other contexts, including investor decisionmaking, and implications for capital markets, see the survey of Daniel, Hirshleifer, and Teoh (2002).

[17]As discussed by Koehler and Mercer (2009), this interpretation is consistent with the dual process theory of cognition (e.g., Kahneman and Frederick (2002)) wherein an automatic, non-deliberative system quickly generates perceptions and judgments based upon environmental stimuli, and a slower, more effortful cognitive system monitors and revises such judgments. Owing to time and cognitive constraints, the slower system does not always come into play, leaving more heuristic judgments in place. This is especially likely to occur for selection bias because adjustment requires attending to *non-occurrences* in the sample construction process, but non-occurrences are less salient and are harder to process than occurrences (see, e.g., Neisser (1963), Healy (1981), and the review of Hearst (1991)).

past performance of a trading strategy tends to convey little information about its future prospects. But investors think otherwise.[18]

We further assume that $r''(R_i) \geq 0$, to capture general evidence that extreme news is more salient than moderate news, and therefore is more often noticed and encoded for later retrieval (Fiske (1980), Moskowitz (2004)). (This assumption is only needed for the model's skewness predictions.) When cognitive processing power is limited, this is a useful heuristic, as extreme news tends to be highly informative. Intuitively, this convexity assumption overlays higher attention to extreme values of R_i on an otherwise-linear relationship between receptiveness and R_i. The salience motivation for convexity of the receiving function is broadly consistent with the attentional explanation given by Barber and Odean (2008) for their finding that individual investors are net buyers of stocks that experience extreme one-day returns of either sign.

We apply a simple polynomial version of these assumptions,

$$r(R_i) = a(R_i)^2 + bR_i + c, \qquad a, b, c \geq 0, \tag{5}$$

under implicit parameter constraints ensuring that for all except arbitrarily small probability of return realizations, r is monotonic and takes value between 0 and 1.

The parameter c measures the susceptibility of receivers to influence, deliberate or otherwise, by the sender. The parameter b reflects the degree to which the receiver tends to naively extrapolate past strategy returns, or at least to be persuaded by high returns. The quadratic parameter a reflects the tendency, after allowing for the effect of b, for extreme returns to be more persuasive.

In this specification, the probability that the receiver is converted is smoothly increasing in the sender return, and is positive even when the sender has a negative return. One

[18] In studies of experimental markets, Smith, Suchanek, and Williams (1988) and Choi, Laibson, and Madrian (2010) provide evidence consistent with investors having extrapolative expectations. In survey evidence, Case and Shiller (1988) report higher expectations of future housing price growth in cities that have experienced past recent price growth; Vissing-Jorgensen (2003) finds that investors with high past portfolio returns expect higher future returns. Using survey and experimental data, DeBondt (1993) reports that the expectations of individual investors follow past trends. Also consistent with excessively extrapolative beliefs, Benartzi (2001) finds that the amount that new contributions by employees to invest in their company's stock increases strongly with the firm's past stock return, but is not a predictor of future returns. There are strong inflows by investors into top-performing mutual funds (Sirri and Tufano (1998)). Barber and Odean (2002) find that early adopters switched to online trading after unusually good performance, and subsequently traded more actively. Greenwood and Nagel (2009) provide evidence that younger mutual fund managers invested heavily in technology stocks during the millennial high-tech boom, presumably owing to extrapolation based on a relatively limited period of market experience. Furthermore, Ederington and Golubeva (2010) find that mutual fund investors reallocate toward stock funds after stock price increases. Dichev and Yu (2011) report that hedge fund investors chase past high returns, resulting in lower performance.

motivation for this is a rational endorsement effect: the very fact that another individual has adopted the trading strategy suggests that he possessed favorable information about it. Furthermore, according to the *mere exposure effect* (Zajonc (1968), Bornstein and D'Agostino (1992), Moreland and Beach (1992)), people like an unreinforced stimulus that they have been exposed to more. This suggests that a receiver who had little prior awareness of the strategy will start to like it more simply by being exposed to it.

Moreover, the *truth effect* is the highly robust finding that people tend to believe more in the truth of debatable statements that they are exposed to more often.[19] This suggests that statements made by the sender in support of the sender's strategy will tend to have some power to persuade receivers.[20]

2.4 Transformation Probabilities

We first examine T_{AP}, the transformation probability for a sender of type A and receiver of type P. By definition,

$$\begin{aligned} T_{AP}(R_A) &= r(R_A)s(R_A) \\ &= (aR_A^2 + bR_A + c)(\beta R_A + \gamma) \\ &= a\beta R_A^3 + BR_A^2 + CR_A + c\gamma, \end{aligned} \tag{6}$$

where

$$\begin{aligned} B &= a\gamma + b\beta \\ C &= b\gamma + c\beta. \end{aligned} \tag{7}$$

Similarly,

$$T_{PA}(R_P) = a\beta R_P^3 + BR_P^2 + CR_P + c\gamma. \tag{8}$$

By assumption, $r', s' > 0$, so $T'_{AP}(R_A), T'_{PA}(R_P) > 0$.

Since the r and s functions are type-independent and the only random variable they depend upon is the sender return, the difference across types in transformation derives from the effect of A versus P on the distribution of sender returns R, as reflected in mean, variance, and skewness.

[19] This applies to both oral or written statements, repetitions separated by minutes or weeks, and settings consisting primarily of either new or repeated statements (Hasher, Goldstein, and Toppino (1977), Schwartz (1982), Hasher, Goldstein, and Toppino (1977), Bacon (1979), Schwartz (1982), Gigerenzer (1984), Hawkins and Hoch (1992), Arkes, Hackett, and Boehm (1989), and Arkes, Boehm, and Xu (1991)).

[20] Another modeling route to the conclusion that even observation of a low return from the sender can sometimes cause a switch would be to have the switch decision depend on the difference in return between sender and receiver, since receiver and sender returns are imperfectly correlated.

2.5 Evolution of Types Conditional on Realized Return

We first show that, owing to SET, high return favors active investing. Given returns R_P and R_A, we can calculate the expected change in the fraction of type A the population after one social interaction between two randomly selected individuals. Recall there are four possible pairing AA, PP, AP, or PA (the first letter denotes the sender, the second the receiver). The change in the frequency of type A given AA or PP is zero. The expected changes in the frequency of type A given a meeting AP or PA and their realized returns are

$$\begin{aligned} E[\Delta f|AP, R_A] &= \left(T_{AP}(R_A) \times \frac{1}{n}\right) + [(1 - T_{AP}(R_A)) \times 0] = \frac{T_{AP}(R_A)}{n} \\ E[\Delta f|PA, R_P] &= \left[T_{PA}(R_P) \times \left(-\frac{1}{n}\right)\right] + [(1 - T_{AP}(R_A)) \times 0] = -\frac{T_{PA}(R_P)}{n}. \end{aligned} \quad (9)$$

So taking the expectation across the different possible combinations of sender and receiver types (AA, PP, AP, PA), by (2) and (9),

$$\left(\frac{2n}{\chi}\right) E[\Delta f|R_A, R_P] = T_{AP}(R_A) - T_{PA}(R_P). \quad (10)$$

So for given returns, the fraction of type A increases on average if and only if $T_{AP}(R_A) > T_{PA}(R_P)$.

Recalling that $T_{AP}(R_A) = s(R_A)r(R_A)$, we can derive some basic predictions of the model from the features of the sending and receiving functions. If R_A and R_P are not perfectly correlated, it is meaningful to examine the effect of increasing R_A with R_P constant. Partially differentiating (10) with respect to R_A twice and using the earlier conditions that $r(R_A), s(R_A), r'(R_A), s'(R_A) > 0$, that $s''(R_A) = 0$ by (4), and that $r''(R_A) > 0$ by (5) gives

$$\left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f|R_A, R_P]}{\partial R_A} = \frac{\partial T_{AP}(R_A)}{\partial R_A} = r'(R_A)s(R_A) + r(R_A)s'(R_A) > 0 \quad (11)$$

$$\left(\frac{2n}{\chi}\right) \frac{\partial^2 E[\Delta f|R_A, R_P]}{\partial (R_A)^2} = \frac{\partial^2 T_{AP}(R_A)}{\partial (R_A)^2} = r''(R_A)s(R_A) + 2r'(R_A)s'(R_A) > 0. \quad (12)$$

Since R_A affects T_{AP} but not T_{PA}, these formulas describe how active return affects both the expected net shift in the fraction of actives, which reflects both inflows and outflows, and the expected unidirectional rate of conversion of passives to actives. An example of a rate of unidirectional conversion would be the rate at which investors who have never participated in the stock market start to participate.

Proposition 1 *If the returns to A and P are not perfectly correlated, both the one-way expected rate of transformation from P to A and the expected change in frequency of A are increasing and convex in return R_A.*

Two studies provide evidence that is broadly consistent with these predictions. Lu (2011) provides evidence that 401(k) plan participants place a greater share of their retirement portfolios in risky investments (equity rather than bond or money market) when their coworkers earned higher equity returns in the preceding period. Kaustia and Knüpfer (2010) report a strong relation between returns and new participation in the stock market in Finland in the range of positive returns. Specifically, in this range, a higher monthly return on the aggregate portfolio of stocks held by individuals in a zip code neighborhood is associated with increased stock market participation by potential new investors living in that neighborhood during the next month. The greater strength of the effect in the positive than in the negative range is consistent with the convexity prediction. Furthermore, within the positive range the effect is stronger for higher returns. The model does not imply a literally zero effect in the negative range, but a weaker effect within this range (as predicted by Proposition 1) could be statistically hard to detect.

Kaustia and Knupfer explain their findings based on what we call SET. Proposition 1 captures this insight, and further reinforcing effects. SET is captured by $s'(R_A) > 0$. The willingness of receivers to convert is increasing with return, as reflected in $r'(R_A) > 0$. By (12), these together contribute to convexity of expected transformation as a function of R_A. A further contributor is the convexity of the receiver function, $r''(R_A)$, reflecting high salience of extreme outcomes.

If we interpret A as participation and active trading in the market for individual stocks with a preponderance of long over short positions, then a rise in the market causes high returns to A investors. Proposition 1 therefore implies that when the stock market rises, volume of trade in individual stocks increases. This implication is consistent with episodes such as the rise of day trading, investment clubs, and stock market chat rooms during the millennial internet boom, and with extensive evidence from 46 countries including the U.S. that investors trade more when stocks have performed well (Statman, Thorley, and Vorkink (2006), Griffin, Nardari, and Stulz (2007)).

2.6 Strategy Return Components

Suppose individual k is of type A and l is of type P. We assume their returns in each period are given by

$$\begin{aligned} R_A^k &= \beta_A r + \epsilon_A^k - D \\ R_P^l &= \beta_P r + \epsilon_P^l, \end{aligned} \tag{13}$$

where r is the common component of returns (e.g., the market portfolio) shared by A and P, the β's is the sensitivity of strategy return to the common return component, and ϵ_A^k and ϵ_P^l are the idiosyncratic return components of strategies A and P respectively, as realized by individuals k and l. The common factor return and idiosyncratic returns are independent over time and independent of each other in the same period. Further, the idiosyncratic returns are assumed to be identical and independently distributed across investors of the same type. All individuals of the same type are ex-ante identical (e.g., they have the same factor loading, same idiosyncratic volatility and skewness), but they differ in the realized idiosyncratic returns (e.g., different actives may hold different stocks).

We denote by μ and σ_r the mean and the standard deviation of the common factor r. We assume $\mu > 0$ and idiosyncratic returns ϵ's have zero means. The active strategy is assumed to have higher systematic risk, $\beta_A > \beta_P \geq 0$. (The condition $\beta_P \geq 0$ is not needed for most of the results.) We further assume that $\sigma_A^2 > \sigma_P^2$, $\gamma_{1A} > 0$, $\gamma_{1P} \approx 0$, and $\gamma_{1r} \geq 0$, where σ_A^2, σ_P^2 are the variances of ϵ_A and ϵ_P, γ_{1r} is the skewness of r, and γ_{1A}, γ_{1P} are the skewnesses of ϵ_A and ϵ_P.

The quantity D in (13) can be thought of as the return penalty (or if negative, premium) to active trading (above and beyond any return difference associated with bearing systematic risk as reflected in β_A and β_P). We call D the return penalty rather than the 'cost' of active trading, because a major part of the utility loss may come from excessive risk-bearing, and the expected return premium associated with the loading on r in our setting is not necessarily what rational investors would demand. So $D < 0$ does not imply that A is better than P. Typically for individual stock investors $D > 0$, since on average they lose money (not just expected utility, and even when benchmarked against standard asset pricing models) from active trading (Barber and Odean (2000b)) or from choosing an actively trading money manager. However, there is also evidence that active investors sometimes outperform passive investors (e.g., Dahlquist, Martinez, and Söderlind (2011)). Our main conclusions apply when $D \leq 0$ as well.

In an explicit model of trading decisions and equilibrium price-setting (see Section 4), risk premia and mispricing affect $E[R_A]$ and $E[R_P]$. In a multiperiod setting, equilibrium

prices and therefore the probability distributions of R_P and R_A generically will fluctuate from period to period. The expected return difference between the two strategies $E[R_A - R_P]$ in general varies over time and depends on the fraction of type A investors. However, it is possible to think of scenarios in which the expected returns do not shift stochastically (e.g., if different A investors merely place side-bets against each other, and therefore do not need to offer a risk premium to persuade P investors to participate in these bets).

Furthermore, in a market equilibrium setting a rise in A in the population is, under appropriate assumptions, self-limiting. As the frequency of A rises, prices will tend to move against the strategies they employ (so long as the A's trade with P's rather than just taking side-bets against each other). The reduction in the expected value to A relative to P would be reflected by a higher expected return differential D. So although the analysis derives conditions under which A increases indefinitely, in an equilibrium setting there will be, apart from random fluctuations, a balanced frequency of A and P.

2.7 Evolution of Types

Many models in evolutionary game theory hypothesize an infinitely large population of interacting agents, usually represented as a continuum. These models often assign revision protocols to agents describing how their behaviors change in response to what they observe, and derive deterministic evolutionary dynamics for the system, in the form of ordinary differential or difference equations (Sandholm (2010)). These equations are expressed in terms of population shares, and the changes are viewed as averages over large numbers of individual strategy switches. In these studies, randomness at the individual level is caused by the matching and the switching processes.

In our model, there is an important additional source of randomness: the payoffs of the strategies. This introduces randomness that is not entirely diversifiable in the cross-section of individuals. Nevertheless, we will exploit the law of large numbers in the time-series to derive deterministic dynamics for the system.

Section 2.5 studies the expected change in the fraction of type A after one round of social interaction between two randomly selected individuals, given their realized returns. In this section, we examine how the unconditional population frequency of A changes over a given time period $[t, t + \Delta]$ after θn pairs of individuals meet when the size of population n approaches infinity (a standing approach for the rest of the paper). We then derive a deterministic dynamics of the frequency of A in the population by letting the length of time period Δ shrink towards zero. This continuous time dynamics is used purely for

tractability, as it offers us a closed form solution for the population dynamics of active investing.

Suppose that over the interval $[t, t+\Delta t]$, θn paired meetings occur occur in sequence. When the population size n approaches infinity, the probability χ of drawing a mixed pair in any one of these meetings is the same and approaches $2f_t(1-f_t)$. Letting ω be an index for the θn meetings, by (10), the change in the population frequency of A is (up to an error that shrinks to zero with n)

$$\begin{aligned} f_{t+\Delta} - f_t &= \left(\frac{\chi}{2n}\right) \sum_{\omega=1}^{\theta n} [T_{AP}(R_{A\omega})] - [T_{PA}(R_{P\omega})] \\ &= \left(\frac{\chi}{2n}\right) \sum_{\omega=1}^{\theta n} a\beta \left(R_{A\omega}^3 - R_{P\omega}^3\right) + B\left(R_{A\omega}^2 - R_{P\omega}^2\right) + C(R_{A\omega} - R_{P\omega}). \end{aligned}$$

Substituting (13) into the above, we have

$$\begin{aligned} f_{t+\Delta} - f_t &= \left(\frac{\chi}{2}\right) \frac{1}{n} \sum_{\omega=1}^{\theta n} a\beta[(\beta_A^3 - \beta_P^3)r^3 + 3r^2(\beta_A^2\epsilon_{A\omega} - \beta_P^2\epsilon_{P\omega}) + 3r(\beta_A\epsilon_{A\omega}^2 - \beta_P\epsilon_{P\omega}^2) + \epsilon_{A\omega}^3 - \epsilon_{P\omega}^3] \\ &\quad + B[(\beta_A^2 - \beta_P^2)r^2 + 2r(\beta_A\epsilon_{A\omega} - \beta_P\epsilon_{P\omega}) + \epsilon_{A\omega}^2 - \epsilon_{P\omega}^2] + C[(\beta_A - \beta_P)r + \epsilon_{A\omega} - \epsilon_{P\omega}] \\ &\quad + D\Delta\{-(r\beta_A + \epsilon_{A\omega})[3a\beta(r\beta_A + \epsilon_{A\omega}) + 2B] - C\} + D^2\Delta^2[3a\beta(r\beta_A + \epsilon_{A\omega}) + B] \\ &\quad -aD^3\Delta^3\beta. \end{aligned} \tag{14}$$

where we have omitted subscripts for the return horizon $(t, t+\Delta)$ from the return variables for brevity ($r = r(t, t+\Delta)$, $R_{A\omega} = R_{A\omega}(t, t+\Delta)$, and $\epsilon_{A\omega} = \epsilon_{A\omega}(t, t+\Delta)$).

Since we assume that returns are i.i.d. over time, the moments of the return distributions are proportional to the length of the return interval $[t, t+\Delta]$. To see this, denote by σ_r, σ_A, σ_P the standard deviation over a unit time interval of the common factor and the idiosyncratic return of the strategy A and P, and γ_{1r}, γ_{1A}, γ_{1P} denote the corresponding skewness. Note that $r(t, t+\Delta) + r(t+\Delta, t+2\Delta) + \cdots + r(t+(m-1)\Delta, t+m\Delta) = r(t, t+1)$, where $m = 1/\Delta$. Since the returns over time are i.i.d.,

$$\begin{aligned} E(r(t, t+\Delta)) &= E(r(t, t+1))\Delta = \mu\Delta \\ E(r(t, t+\Delta)^2) &= E(r(t, t+1)^2)\Delta = (\mu^2 + \sigma_r^2)\Delta \\ E(r(t, t+\Delta)^3) &= E(r(t, t+1)^3)\Delta = (\mu^3 + 3\mu\sigma_r^2 + \sigma_r^3\gamma_{1r})\Delta. \end{aligned} \tag{15}$$

A similar argument shows that the idiosyncratic returns satisfy $E(\epsilon_i(t, t+\Delta)^2) = \sigma_i^2\Delta$, and $E(\epsilon_i(t, t+\Delta)^3) = \sigma_i^3\gamma_{1i}\Delta$, $i = A, P$.

When the population size n approaches infinity, by the law of large numbers the randomness coming from the matching process and from individual-specific return components average out. This allows replacing all ϵ terms in (14) with their expected values. We therefore obtain

$$\begin{aligned}\frac{f_{t+\Delta}-f_t}{\theta f_t(1-f_t)} &= a\beta[(\beta_A^3-\beta_P^3)r^3+3r(\beta_A\sigma_A^2-\beta_P\sigma_P^2)\Delta+(\gamma_{1A}\sigma_A^3-\gamma_{1P}\sigma_P^3)\Delta] \\ &+ B[(\beta_A^2-\beta_P^2)r^2+(\sigma_A^2-\sigma_P^2)\Delta]+C(\beta_A-\beta_P)r \\ &-D\Delta[3a\beta\beta_A^2r^2+3a\beta\sigma_A^2\Delta+2B\beta_Ar+C]+D^2\Delta^2(3a\beta r\beta_A+B)-aD^3\Delta^3\beta.\end{aligned} \tag{16}$$

The common factor return $r = r(t, t+\Delta)$ does not diversify across individuals for a given fixed horizon Δ. However, we can subdivide $[t, t+\Delta]$ into arbitrarily large number of smaller time intervals, and apply the law of large numbers over returns of non-overlapping time periods. Then we let $\Delta \to 0$, and obtain deterministically the local rate of change in f, defined as $lim_{\Delta\to 0}(f_{t+\Delta}-f_t)/\Delta$.

More precisely, we divide $[t, t+\Delta]$ into h smaller intervals each of length δ with $h\delta = \Delta$. Then $f_{t+\Delta}-f_t = \sum_{i=1}^h [f_{t+i\delta}-f_{t+(i-1)\delta}]$. Applying equation (16) to each $f_{t+i\delta}-f_{t+(i-1)\delta}$ gives

$$\begin{aligned}f_{t+\Delta}-f_t &= \theta\sum_{i=1}^h[f_{t+(i-1)\delta}(1-f_{t+(i-1)\delta})]\{a\beta[(\beta_A^3-\beta_P^3)r_i^3+3r_i(\beta_A\sigma_A^2-\beta_P\sigma_P^2)\delta \\ &+ (\gamma_{1A}\sigma_A^3-\gamma_{1P}\sigma_P^3)\delta]+\ B[(\beta_A^2-\beta_P^2)r^2+(\sigma_A^2-\sigma_P^2)\delta]+C(\beta_A-\beta_P)r_i \\ &- D\delta[3a\beta\beta_A^2r_i^2+3a\beta\sigma_A^2\delta+2B\beta_Ar_i+C]+D^2\delta^2(3a\beta r_i\beta_A+B)-aD^3\delta^3\beta\},\end{aligned}$$

where r_i denotes the common factor return over $[t+(i-1)\delta, t+i\delta]$. As $h \to \infty$ (i.e., $\delta \to 0$), since returns are identical and independent over all the intervals, we can apply the law of large numbers over time and replace the summations involving r, r^2, and r^3 by their expected values as given in (15):

$$\begin{aligned}\sum_{i=1}^h r_i &= hE(r_i)=E(r)=\mu\Delta \\ \sum_{i=1}^h r_i^2 &= hE(r_i^2)=E(r^2)=(\mu^2+\sigma_r^2)\Delta \\ \sum_{i=1}^h r_i^3 &= hE(r_i^3)=E(r^3)=(\mu^3+3\mu\sigma_r^2+\sigma_r^3\gamma_{1r})\Delta.\end{aligned}$$

For all i, $f_{t+(i-1)\delta}(1-f_{t+(i-1)\delta})$ can be approximated by $f_t(1-f_t)$, with the error terms shrinking to zero as Δ approaches zero. Thus, in an infinite population, first letting the

number of subdivisions of Δ approach infinity, and then letting $\Delta \to 0$, we derive the continuous-time evolutionary dynamic of the population frequency of type A as an ordinary differential equation,

$$\frac{df}{dt} = \theta f(1-f)K, \tag{17}$$

where K is a constant which depends on the model parameters that characterize the sending and receiving function, and the return distribution of each strategy,

$$\begin{aligned} K &= a\beta[(\beta_A^3 - \beta_P^3)(\mu^3 + 3\mu\sigma_r^2 + \sigma_r^3\gamma_{1r}) + (\gamma_{1A}\sigma_A^3 - \gamma_{1P}\sigma_P^3)] \\ &+ B[(\beta_A^2 - \beta_P^2)(\mu^2 + \sigma_r^2) + (\sigma_A^2 - \sigma_P^2)] \\ &+ C[(\beta_A - \beta_P)\mu - D]. \end{aligned} \tag{18}$$

Solving (17) for f as a function of t under the initial condition that at date 0 the fraction of type A investors is f_0, we obtain

$$f(t) = \frac{\psi e^{\theta K t}}{1 + \psi e^{\theta K t}}, \tag{19}$$

where ψ is a monotonic transformation of f_0, $\psi = f_0/(1-f_0)$.

The solution for K in (18) lets us calculate comparative statics of the system at any time t. It also allows us to determine whether there is a stable interior fraction of active investors, and if so, the comparative statics of its level.

2.7.1 Comparative Statics

The evolution of the population frequency of A is governed by K in (18). To gain insight into the determinants of the reproductive success of A versus P strategies, we describe comparative statics effects on the fraction of actives in the population. These comparative statics are obtained by taking the partial derivatives of K with respect to various model parameters, under the assumptions that $\mu > 0$, $\beta_A > \beta_P$, $\sigma_A^2 > \sigma_P^2$, $\gamma_{1r} \geq 0$, $\gamma_{1A} > 0$, $\gamma_{1P} \approx 0$.

Letting $t = 0$, and given some initial frequency of type A at this date, we obtain:

Proposition 2 *Under the parameter constraints of the model (parts 9-12: and under the further constraint that $D < (\beta_A - \beta_P)\mu$), for any given time $t > 0$, the population frequency of A*

1. *Decreases with the return penalty to active trading D;*

2. *Increases with the mean return of the common factor μ;*

3. *Increases with factor skewness, γ_{1r};*

4. *Increases with active idiosyncratic skewness, γ_{1A}; and decreases with passive idiosyncratic skewness, γ_{1P}, so long as $\sigma_P \neq 0$;*

5. *Increases with active idiosyncratic volatility, σ_A; and decreases with passive idiosyncratic volatility, σ_P, so long as $\sigma_P \neq 0$ and γ_{1P} is not too negative;*

6. *Increases with the factor loading of the active strategy, β_A, and decreases with the factor loading of the passive strategy, β_P;*

7. *Increases with the variance of the common factor, σ_r^2;*

8. *Increases with attention of receivers to extremes, a;*

9. *Increases with SET, β;*

10. *Increases with the sensitivity of receptiveness to returns, b;*

11. *Increases with the sender conversability, γ, of trading strategies;*

12. *Increases with the susceptibility of receivers, c.*

Before proving these results and providing the intuition, observe that by (19), so long as $0 < f_0 < 1$, the population frequency of A is monotonically increasing with K. Thus, to obtain the comparative statics in Proposition 2, we need only obtain the partial derivatives of K with respect to the model parameters.

Also, if we view the active strategy as the choice of investments with certain risk characteristics such as high volatility or skewness based upon overoptimism about certain stocks, then the predictions in Proposition 2 about the frequency of A becomes a prediction that such stocks become overpriced. Specifically, the equilibrium model of Section 4 assumes that the actives have overoptimistic beliefs about high volatility assets, whereas passive investors have rational expectations, and shows that the evolution toward active investing depresses the expected returns of the risky assets. In discussing here the partial equilibrium comparative statics predictions about the frequency of A, we will make use of the intuitive extension (motivated by the equilibrium model) to draw predictions about expected returns.

To show Part 1, we differentiate K with respect to D, the return penalty to active trading, to obtain

$$\frac{\partial K}{\partial D} = -C < 0. \tag{20}$$

So the success of A decreases with D, i.e., a greater return penalty to active trading makes A less contagious.

For Part 2, differentiating with respect to the mean factor return μ gives

$$\frac{\partial K}{\partial \mu} = a\beta(\beta_A^3 - \beta_P^3)(3\mu^2 + 3\sigma_r^2) + 2B(\beta_A^2 - \beta_P^2)\mu + C(\beta_A - \beta_P) > 0 \tag{21}$$

Other things equal, the higher the mean return of the common factor, the larger the performance difference between active and passive strategies trading, because of the higher factor loading of the active strategy. Owing to SET, higher mean return to the common factor helps the spread of active trading.

For Part 3, differentiating with respect to factor skewness γ_{1r} gives

$$\frac{\partial K}{\partial \gamma_{1r}} = a\beta\sigma_r^3(\beta_A^3 - \beta_P^3) > 0 \tag{22}$$

since $\beta_A > \beta_P$. Thus, the advantage of A over P is increasing with factor skewness. Intuitively, extreme high returns are especially likely to be sent, noticed, and to convert the receiver when noticed. Since A has a greater factor loading than P, factor skewness is magnified in A relative to P, making A more contagious.

For Part 4, differentiating with respect to active idiosyncratic skewness γ_{1A} gives

$$\frac{\partial K}{\partial \gamma_{1A}} = a\beta\sigma_A^3 > 0. \tag{23}$$

Thus, the advantage of A over P is increasing with the idiosyncratic skewness of A. The intuition is similar to that of Part 3.

Differentiating with respect to passive idiosyncratic skewness γ_{1P} gives

$$\frac{\partial K}{\partial \gamma_{1P}} = -a\beta\sigma_P^3, \tag{24}$$

which is negative so long as $\sigma_P \neq 0$

Part 4 implies that conversation especially encourages demand for securities with high skewness. Mitton and Vorkink (2007) document that underdiversified investors tend to choose stocks with high skewness–especially idiosyncratic skewness. Goetzmann and Kumar (2008) find that underdiversified investors tend to prefer stocks that are volatile and positively skewed.

Examples of skewed securities include options or 'lottery stocks', such as loss firms (Teoh and Zhang (2012)) or real option firms that have a small chance of a jackpot outcome. There is evidence that ex ante return skewness is a negative predictor of future stock

returns (Conrad, Dittmar, and Ghysels (2009), Eraker and Ready (2010)). There is also evidence from initial public offerings (Green and Hwang (2010)) and general samples (Bali, Cakici, and Whitelaw (2009)) that lottery stocks are overpriced, and that being distressed (a characteristic that leads to a lottery distribution of payoffs) on average predicts negative abnormal returns (Campbell, Hilscher, and Szilagyi (2008)). Boyer and Vorkink (2011) find that the ex ante skewness of equity options is a negative cross-sectional predictor of option abnormal returns.

In the model of Brunnermeier and Parker (2005), agents who optimize over beliefs prefer skewed payoff distributions. In the model of Barberis and Huang (2008), prospect theory preferences with probability weighting creates a preference over portfolio skewness. This induces a demand for 'lottery' (high idiosyncratic skewness) stocks by virtue of their contribution to portfolio skewness. Our approach differs in that there is no inherent preference for skewness. Instead, bias in the transmission process cause the holding of lottery stocks to be contagious.

This difference results in distinct empirical implications about trading in lottery stocks. In our setting, greater social interaction increases contagion, thereby increasing the holdings of lottery stocks. For example, individuals with greater social connection (as proxied, for example, by population density, participation in investment clubs, or regular church-going) will favor such investments more.

Consistent with a possible effect of social contagion, individuals who live in urban areas buy lottery tickets more frequently than individuals who live in rural areas (Kallick et al. (1979)). Furthermore, there is evidence suggesting that the preference for high skewness stocks is greater among urban investors, after controlling for demographic, geographic, and personal investing characteristics (Kumar 2009).[21]

A further intuitive empirical implication is that more credulous individuals will tend to invest more in high variance and lottery stocks owing to the influence of conversation as compared with more skeptical individuals. Such differences could arise from differences in general intelligence or in the psychological propensity to trust that others are not behaving strategically in their choice of what to communicate. This prediction goes beyond the strict bounds of the model, as it requires heterogeneous individuals.

For Part 5, differentiating with respect to active idiosyncratic volatility σ_A gives

$$\frac{\partial K}{\partial \sigma_A} = 3a\beta\gamma_{1A}\sigma_A^2 + 2B\sigma_A > 0. \tag{25}$$

[21]Kumar (2009) empirically defines lottery stocks as stocks with high skewness, high volatility, and low price. His findings therefore do not distinguish the effects of skewness versus volatility.

Thus, the frequency of A increases with active idiosyncratic volatility σ_A. Greater return variance increases the effect of SET on the part of the sender. Although not required for it, the salience to receivers of extreme returns as reflected in the a term reinforces this effect, since it is the extreme high returns that are disproportionately communicated.

The finding of Goetzmann and Kumar (2008) discussed above, that underdiversified investors tend to prefer stocks that are more volatile, is consistent with Part 5. A further empirical implication of Part 5 is that in periods in which individual stocks have high idiosyncratic volatility, *ceteris paribus* there will be greater holding of and trade in individual stocks. Intuitively, during such periods A's have more large gains to report selectively. This implication is in sharp contrast with the prediction of portfolio theory, which suggests that in periods of high idiosyncratic volatility, the gains to holding a diversified portfolio rather than trading individual stocks is especially large. Tests of this prediction would therefore be useful for distinguishing alternative hypotheses.

Differentiating with respect to passive idiosyncratic volatility σ_P gives

$$\frac{\partial K}{\partial \sigma_P} = -3a\beta\gamma_{1P}\sigma_P^2 - 2B\sigma_P, \tag{26}$$

which is negative if $\sigma_P > 0$ and γ_{1P} is positive or not too negative. Passive idiosyncratic volatility encourages the spread of P at the expense of A owing to self-enhancing transmission bias, as reflected in the B term.

The idiosyncratic volatility puzzle is the finding that stocks with high idiosyncratic risk earn low subsequent returns.[22] There is also evidence that this apparent overpricing is stronger for firms held more heavily by retail investors (Jiang, Xu, and Yao (2009)), for whom we would expect conversational biases to be strong. The comparative statics on idiosyncratic volatility offers a possible explanation for the puzzle, based upon social interactions: high returns on volatile stocks are heavily discussed, which increases the demand for such stocks, driving up their prices.

An alternative possibility is that individual-level biases such as realization utility or prospect theory with probability weighting create a preference for volatile portfolios and stocks (Barberis and Xiong (2010), Boyer, Mitton, and Vorkink (2010)). However, consistent with a possible effect of social contagion, there is evidence suggesting that the preference for high volatility is greater among urban investors after extensive controls (Kumar (2009)).

[22]This is documented by Ang et al. (2006, 2009), Bali, Cakici, and Whitelaw (2009), Huang et al. (2010)), Boyer, Mitton, and Vorkink (2010), Conrad, Dittmar, and Ghysels (2009), and Baker, Bradley, and Wurgler (2010).

For Part 6, differentiating with respect to the factor loading of the active strategy, β_A, gives

$$\frac{\partial K}{\partial \beta_A} = 3a\beta\beta_A^2(\mu^3 + 3\mu\sigma_r^2 + \sigma_r^3\gamma_{1r}) + 2\beta_A B(\mu^2 + \sigma_r^2) + C\mu > 0. \tag{27}$$

So a greater factor loading for A increases the evolution toward A, since the wider distribution of return outcomes encourages the sending of high, influential returns. Baker, Bradley, and Wurgler (2010) report that in the U.S., high beta stocks have substantially underperformed low beta stocks over the past 41 years, which is consistent with investors excessively favoring investment in stocks with high loadings.

Similarly, differentiating with respect to the factor loading of the passive strategy, β_P gives

$$\frac{\partial K}{\partial \beta_P} = -3a\beta\beta_P^2(\mu^3 + 3\mu\sigma_r^2 + \sigma_r^3\gamma_{1r}) - 2\beta_P B(\mu^2 + \sigma_r^2) - C\mu < 0. \tag{28}$$

So a greater factor loading for P opposes the evolution toward A, since the wider distribution of return outcomes encourages the spread of P.

For Part 7, differentiating with respect to the standard deviation of the common factor, σ_r gives

$$\frac{\partial K}{\partial \sigma_r} = 3a\beta(\beta_A^3 - \beta_P^3)(2\mu\sigma_r + \gamma_{1r}\sigma_r^2) + 2B(\beta_A^2 - \beta_P^2)\sigma_r > 0 \tag{29}$$

since $\beta_A > \beta_P$. So greater volatility of the common factor favors evolution toward A, since both more extreme right tail and the wider distribution of return outcomes encourage the spread of the strategy with the greater loading, A, by creating greater scope for SET to operate.

This implies that *ceteris paribus* there will be greater stock market participation in time periods and countries with more volatile stock markets. As discussed earlier in the context of idiosyncratic volatility, this is surprising from the perspective of conventional theory, which implies that greater risk reduces the benefit to participation. So the analysis suggests that bubble periods attract greater investor participation in speculative markets in part *because* of, not despite, high market volatility.

Overall, the findings on factor loadings and the different components of volatility suggest that volatility will be overvalued in the economy. As such, the explanation for the equity premium puzzle—the high returns on the U.S. equity market—clearly lies outside the model, though not necessarily beyond the realm of other possible cultural evolutionary explanations.

For Part 8, recall that the quadratic term of the receiving function a reflects greater attention on the part of the receiver to extreme profit outcomes communicated by the sender. Differentiating with respect to a gives

$$\begin{aligned}\frac{\partial K}{\partial a} &= \beta[(\beta_A^3 - \beta_P^3)(\mu^3 + 3\mu\sigma_r^2 + \sigma_r^3\gamma_{1r}) + (\gamma_{1A}\sigma_A^3 - \gamma_{1P}\sigma_P^3)] \\ &+ \gamma[(\beta_A^2 - \beta_P^2)(\mu^2 + \sigma_r^2) + (\sigma_A^2 - \sigma_P^2)] \\ &> 0. \end{aligned} \tag{30}$$

So greater attention by receivers to extreme outcomes, a, promotes the spread of A over P because A generates more of the extreme returns which, when a is high, are especially noticed. This effect is reinforced by SET, which causes greater reporting of extreme high returns.

For Part 9, differentiating with respect to β, the strength of SET (reflecting, for example, how tight the link is between the sender's self-esteem and performance), and recalling by (7) that B is an increasing function of β, gives

$$\begin{aligned}\frac{\partial K}{\partial \beta} &= a[(\beta_A^3 - \beta_P^3)(\mu^3 + 3\mu\sigma_r^2 + \sigma_r^3\gamma_{1r}) + (\gamma_{1A}\sigma_A^3 - \gamma_{1P}\sigma_P^3)] \\ &+ b[(\beta_A^2 - \beta_P^2)(\mu^2 + \sigma_r^2) + (\sigma_A^2 - \sigma_P^2)] + c[(\beta_A - \beta_P)\mu - D] \\ &> 0 \end{aligned} \tag{31}$$

if D is not too large. So greater SET increases the evolution toward A if the return penalty to active investing is not too large, because SET causes greater reporting of the high returns that make A enticing for receivers. A generates high returns through higher factor loading, idiosyncratic volatility, or more positive idiosyncratic skewness.

This comparative statics suggests a cross-cultural prediction that the tendency to evolve toward A should be weaker in Asian culture, which places a heavy premium on humility, than in Western culture. Of course any test of this hypothesis would need to control for many other differences, including demographic factors and cross-cultural differences in individual-level risk-taking propensities and belief in luck.

For Part 10, differentiating with respect to the sensitivity of receptiveness to returns b gives

$$\begin{aligned}\frac{\partial K}{\partial b} &= \beta[(\beta_A^2 - \beta_P^2)(\mu^2 + \sigma_r^2) + (\sigma_A^2 - \sigma_P^2)] + \gamma[(\beta_A - \beta_P)\mu - D] \\ &> 0 \end{aligned} \tag{32}$$

if the return penalty to active investing D is not too large. Greater sensitivity of receivers to returns helps A spread by magnifying the effect of SET (reflected in β), which helps

A because of the higher spread in the returns of A. The analysis therefore implies, for example, that when extrapolative beliefs are stronger (past returns are perceived to be more informative about the future), the culture will tend to evolve toward active trading.

For Part 11, differentiating with respect to sender conversability γ gives

$$\begin{aligned} \frac{\partial K}{\partial \gamma} &= a[(\beta_A^2 - \beta_P^2)(\mu^2 + \sigma_r^2) + (\sigma_A^2 - \sigma_P^2)] + b[(\beta_A - \beta_P)\mu - D] \\ &> 0 \end{aligned} \tag{33}$$

if the return penalty to active investing D is not too large. Greater conversability γ helps the active strategy spread in part because of the greater attention paid by receivers to extreme returns ($a > 0$). Extreme returns are more often generated by the A strategy. So a greater unconditional propensity to report returns tends to have a greater influence when the sender is A.

In addition, the b term shows that greater conversability further helps the spread of A if on average A earns higher returns, $(\beta_A - \beta_P)\mu - D > 0$. If, however, A earns lower returns than P, the effect from the b term opposes the spread of A, because the increase in conversation is spreading relatively bad news about A.

Overall, under the conditions of Part 11, the model implies that active trading will tend to increase with proxies for the unconditional tendency for people to talk about their investment performance. For example, the rise of communication technologies, media, and such social phenomena as ubiquitous cell phones, stock market chat rooms, investment clubs, and blogging should favor active trading. This suggests that the rise of these phenomena may have contributed to the millennial internet bubble.

If greater social interaction is associated with greater comfort in discussing performance information, then in any given conversation it increases the unconditional probability that the sender will discuss returns; i.e., it increases γ. So under the relevant parameter restrictions the model implies that this will increase evolution toward active trading. In a study of 49 countries, Eleswarapu (2004) reports that stock market turnover is higher in countries with greater population density after controlling for legal and political institutions and income.

There is also survey evidence consistent with an effect of differences in social interaction within society on stock market participation (Hong, Kubik, and Stein (2004)). The degree of social interactiveness is measured by self-reports of interacting with neighbors and of attending church. Socials were more likely to invest in the stock market after controlling for wealth, race, education and risk tolerance. Furthermore, survey evidence from ten

European countries indicates that household involvement in social activities increases stock market participation (Georgarakos and Pasini (2011)).

Lastly, for Part 12 of the Proposition, differentiating with respect to the susceptibility of receivers, c, gives

$$\begin{aligned} \frac{\partial K}{\partial c} &= \beta[(\beta_A - \beta_P)\mu - D] \\ &> 0 \end{aligned} \tag{34}$$

if the return penalty to active investing D is not too large. The reason is that greater susceptibility increases the likelihood that the receiver is transformed *given that* the sender sends. Owing to SET (as reflected in the β term above), the effect of receiver susceptibility on the fraction of A type depends on the difference in the probability that A sends and the probability that P sends. When $D < (\beta_A - \beta_P)\mu$, the actives on average outperform the passives, so the sending probability by type A is higher. Later, our equilibrium analysis implies that A on average underperforms P, so the lesson we take from Part 12 is actually the opposite statement, that greater c reduces f. So an implication of this reversed Part 12 is that (if actives on average underperform), then higher pressures toward conformity (hence, more susceptible receivers) are actually beneficial in helping the culture evolve away from costly, return-reducing active strategies.

The model further predicts that there will be overvaluation of stocks with 'glamour' characteristics that make them attractive topics of conversation, such as growth, recent IPO, high idiosyncratic volatility, sports, entertainment, media, and innovative consumer products. In contrast, there should be neglect and underpricing of unglamourous firms that are less attractive topics of conversation, such as business-to-business vendors or suppliers of infrastructure.[23] Conversational transmission biases can therefore help explain several well known empirical puzzles about investor trading and asset pricing.

Related predictions about the effects of investor attention have been made before (Merton (1987)). A distinctive feature here is that the prediction is based on social interaction. These effects should therefore be stronger in times and places with higher social interaction. This point provides additional empirical predictions about the effects on return anomalies of population density, urban versus rural localities, pre- and post-internet periods, national

[23]Loughran and Ritter (1995) document underperformance of IPOs and other equity-issuing firms. The underperformance of growth firms is especially strong among the smallest quintile of firms (Fama and French (1993)), which disproportionately includes IPO firms. Ang et al. (2006, 2009) document that high volatility negatively predicts returns in the cross section.

differences in self-reported degrees of social interaction, popularity of investment clubs and chat rooms, and so forth.

2.7.2 The Evolutionary Success of Active Investing

The intuition underlying the comparative statics provides insight into the basic issue of whether evolution favors A or P. In (19), the long-run behavior of the population frequency of type A is determined by the sign of K. If $K > 0$, then $f(t) \to 1$ as $t \to \infty$ (i.e., type A dominates eventually); if $K < 0$, then $f(t) \to 0$ as $t \to \infty$ (i.e., type P dominates eventually). The magnitude of K governs the speed at which the system moves to the long-run target. For example, when K is positive, the larger it is, the faster the active investor population grows.

Proposition 3 *Under the parameter constraints of the model, if the return penalty to active trading D is sufficiently small ($D < (\beta_A - \beta_P)\mu$), then over time active investing will dominate the population.*

This outcome results from a combination of the effects of the higher factor loading β_i, idiosyncratic skewness γ_{1i}, and idiosyncratic volatility σ_i of A over P, as explained in the discussion of the comparative statics. A strategy that is more volatile (either because of greater loading on a factor or because of idiosyncratic risk) magnifies the effect of SET in persuading receivers to the strategy. Owing to greater attention to extremes, skewness (which generates strongly noticed high returns) further reinforces the success of A.

In general, models in which there is contagious adoption of innovations lead to S-shaped adoption curves (Griliches (1957), Young (2009)). In the model here, the adoption curve in (19) starting from a low frequency of A, as would occur when a new form of active trading becomes available, is S-shaped. In contrast with contagious processes of adoption, other forms of adoption (such as independent trial and error experimentation) in general do not yield S-shaped adoption curves (Henrich (2001)).

As compared with professional money managers, individual investors are probably more strongly influenced by social interactions rather than independent analysis and investigation. This suggests that the predictions of Propositions 2 and 3 that social interaction favors active investing will apply more strongly to individual investors. Individual investors do tend to favor small stocks, which tend to be volatile. Of course, financial institutions do more trading in relatively complex securities such as derivatives, but there are other obvious reasons why more sophisticated players would invest in more complex securities.

Transmission bias has broader implications for the evolution of active trading. One implication of the model is that greater frequency of conversation implies more rapid evolution toward active trading. Trading outcomes are a trigger for conversation about trading, so over time as markets become more liquid and trading becomes more frequent, we expect conversation about outcomes to become more frequent. Reporting and discussion of financial markets has become more available and salient on television and through the internet, which should also trigger greater conversation about performance news and therefore more rapid evolution toward more active investing.

2.7.3 An Alternative Specification for the Receiving Function

We have assumed that the individual receiver is influenced only by the sender's return, not his own. This assumption is an oversimplification. Implicitly, to the extent there is a common component in the returns of the sender and receiver, the receiver already takes into consideration his own return. Here we examine alternative specification where we explicitly assume that the receiving function depends on the difference in returns between the sender and the receiver: when a sender of type A meets with a receiver of type P and communicates return R_A, P (whose return is R_P) is converted to type A with probability $r_{AP}(R_A) = a(R_A - R_P)^2 + b(R_A - R_P) + c$.

Under this alternative specification, the continuous-time dynamics of the population frequency of type A is still of the form given in (17), except the rate of change K is now:

$$\begin{aligned} K &= a\beta[(\beta_A - \beta_P)(\beta_A^2 + \beta_P^2)(\mu^3 + 3\mu\sigma_r^2 + \sigma_r^3\gamma_{1r}) + (\gamma_{1A}\sigma_A^3 - \gamma_{1P}\sigma_P^3)] \\ &+ B'[(\beta_A^2 - \beta_P^2)(\mu^2 + \sigma_r^2) + (\sigma_A^2 - \sigma_P^2)] + C'[(\beta_A - \beta_P)\mu - D], \end{aligned} \tag{35}$$

where

$$\begin{aligned} B' &= b\beta \\ C' &= 2b\gamma + c\beta. \end{aligned} \tag{36}$$

It is straightforward to verify that Propositions 1, 2 and 3 remain valid when the receiving function depends on the relative return between the sender and the receiver.

2.8 Local Bias and Familiarity Bias

Proximate and familiar events and issues are attractive topics of conversation; the fascination with the local and familiar is also reflected in local reporting in the news media. There is evidence that in deliberation people talk more about information that is already

shared than about information that is unique to an individual (e.g., Stasser and Titus (1985), Stasser, Taylor, and Hanna (1989)). Fast, Heath, and Wu (2009) find that people prefer to find common ground in conversations by discussing jointly familiar topics. So in meetings with fellow locals, we expect locally familiar firms to be perceived as legitimate and attractive topics for conversation.

A generalization of the model to include local and non-local investors generates local investment biases. In such a setting, the high conversability of local stocks to local investors combined with the tendency of local investors to talk to each other, promotes local stock trading and holding.

Consider a setting in which there are two assets, an individual stock and the market portfolio, and in which some investors ('locals') are located near the firm's headquarters and some ('outsiders') are not. Locals find the stock more conversable than do outsiders. Let A be investing in the stock, and P be holding the market portfolio.

Assume further that locals and outsiders never talk to each other, so that we can apply the basic model separately to locals and outsiders. (We do not consider how equilibrium prices are determined by the local and outside supplies and demands for the stock and for the market index.) Then the higher conversability of the local stock implies a stronger tendency for the local than for the outsider population to evolve toward A. For some parameter values, the analysis of earlier sections implies that local investors invest in the local stock and outsiders do not.

Result 1 *In the model of this subsection, there exists a non-empty open set of parameter values such that the local population evolves toward A, and the outsider population will evolve toward P.*

As proof, consider the values $\beta_A = 1.2, \beta_P = 1, \sigma_r = 0.2, \sigma_A = 0.4$, $\sigma_P = 0$, and $\gamma_{1r} = \gamma_{1A} = \gamma_{1P} = 0$. These parameter values do not seem empirically implausible. Let the parameters for the sending and receiving functions be $a = 5$, $b = 1$, $c = 0.5$, and $\beta = 5$.

Let the two populations differ only in the conversability parameter γ; let $\gamma = 0.6$ for local investors and $\gamma = 0.2$ for outsiders. Then $E[T_{AP}(R_A) - T_{PA}(R_P)] = 0.1692$, $E[T_{AP}(R_A) - T_{PA}(R_P)] = -0.0310$. Thus, on average the fraction of investors within the local population who hold the individual stock increases, whereas for outsiders the population shifts towards holding the market portfolio. So an avoidance by outsiders of the stock need not be driven by any fear, aversion, or unawareness on their part about it. A high conversibility of local stocks to locals is enough to drive 'home bias' on the part of outsiders.

There is evidence of familiarity and local biases in investing, as with home bias in favor of domestic over foreign stocks (Tesar and Werner (1995)). Huberman (2001) provides evidence that investors tend to choose locally familiar stocks. The analysis here implies that such effects will be stronger when social interaction is more geographically localized. This suggests that the rise of new forms of internet communication such as social networking websites should reduce local bias.

A plausible further assumption is that naive investors are more prone to be influenced in their investment decisions by conversation. It also seems plausible that such investors tend to be linked more strongly to their local investor social network than to society at large. In either case, it follows that naive investors will have stronger local bias. Goetzmann and Kumar (2008) document that younger, less wealthy, and less sophisticated investors tend to favor locally based stocks. These findings are consistent with the local bias theory provided here.

Finally, this analysis can alternatively be reinterpreted as reflecting clustering in a conversational social network that occurs for conceptual rather than of geographical reasons. We can view locals as those who are more familiar with an investment, and outsiders as those who are less familiar with it. If we further assume that those who are familiar with it are especially prone to talking about it to each other as compared with outsiders, a similar implication follows that those who are more familiar with the investment invest more in it.

For example, employees often voluntarily hold company stock, sacrificing diversification. It seems quite plausible that a firm's employees talk to each other—even to geographically distant fellow employees—more than they talk to random outside members of the population. So conversational bias can explain the company stock puzzle.

3 Endogenizing the Receiving and Sending Functions

We now consider explicitly the determinants of the sending and receiving functions, and derive the assumed functional forms endogenously.

3.1 The Sending Function

To derive a sending function that reflects the desire to self-enhance, we assume that the utility derived from sending is increasing with own-return. Conversation is an occasion for an individual to try to raise the topic of return performance if it is good, or to try to avoid the topic if it is poor. Suppressing i subscripts, let $\pi(R, x)$ be the utility to the sender of

discussing his return R,

$$\pi(R, x) = R + \frac{x}{\beta'}, \tag{37}$$

where β' is a positive constant, and random variable x measures whether, in the particular social and conversational context, raising the topic of own-performance is appropriate or even obligatory.

The sender sends if and only if $\pi > 0$, so

$$\begin{aligned} s(R) &= Pr\left(x > -\beta' R | R\right) \\ &= 1 - F(-\beta' R), \end{aligned} \tag{38}$$

where F is the distribution function of x. If $x \sim U[\tau_1, \tau_2]$, where $\tau_1 < 0, \tau_2 > 0$, then

$$\begin{aligned} s(R) &= \frac{\tau_2 + \beta' R}{\tau_2 - \tau_1} \\ &= \frac{\tau_2}{\tau_2 - \tau_1} + \beta R, \end{aligned} \tag{39}$$

where $\beta \equiv \beta'/(\tau_2 - \tau_1)$, and where we restrict the domain of R to satisfy $-\tau_2/\beta' < R < \tau_1/\beta'$ to ensure that the sending probability lies between 0 and 1. This will hold almost surely if $|\tau_1|, |\tau_2|$ are sufficiently large. Equation (39) is identical to (4) in Subsection 2.2 with

$$\gamma \equiv \frac{\tau_2}{\tau_2 - \tau_1}.$$

3.2 The Receiving Function

A convex increasing shape for the receiving function can derive from the combination of two effects: greater receiver attention to extreme return outcomes (inducing convexity), and, conditional upon paying attention, greater persuasiveness of higher return. When we model the attention to extreme outcomes with a quadratic function, and then multiply this by a linear increasing function to reflect the monotonic effect of attractiveness, the result is a cubic form for the receiving function. The quadratic specification used in Section 2, which is more tractable, can be viewed as a Taylor approximation to the cubic.

Greater attention to extreme outcomes can be captured by having receiver attention be a positive quadratic function of the sender's return,

$$A(R) = c_1 R^2 + c_2, \qquad c_1, c_2 > 0.$$

Conditional on the receiver attending, assume that the receiver's probability of converting to the sender's type is an increasing linear function of sender return,

$$B(R) = e_1 R + e_2, \qquad e_1, e_2 > 0.$$

In other words, the receiver interprets sender return as providing information about the desirability of the sender's strategy. This inference may be largely invalid, but is tempting, as reflected in the need for the standard warning to investors that "past performance is no guarantee of future results." The 'law of small numbers' (Tversky and Kahneman 1971) is the psychological finding that individuals overweight evidence from small sample sizes in drawing inferences about the underlying distributions. This is a consequence of representativeness (Tversky and Kahneman (1974)), the tendency to expect similarity between the characteristics of a sample and the underlying population.

The law of small numbers should attenuate the degree to which receivers discount for a sender's upward selection in reporting returns. A receiver who thinks that even a single return observation is highly informative will adjust less for sender suppression of bad news. For example, in the limiting case in which one return observation is viewed as conclusive about the strategy's quality, selection bias notwithstanding, a favorable return report will be taken at face value.

As with the law of small numbers, the vividness of personal stories causes insufficient discounting of selection bias. People tend to neglect the abstract information contained in 'base rates' (general statistical information about the population) in favor of small samples of vivid cases (Borgida and Nisbett (1977)).[24]

With these assumptions on the A and B functions,

$$r(R) = A(R)B(R)$$

is a cubic function with positive coefficients. This implies positive coefficients on the quadratic Taylor approximation to $r(R)$, as in equation (5).

4 Equilibrium Trading and Returns

So far we have considered a general notion of activity versus passivity in which A can refer to either some static action such as holding a given risky asset, or to a general dynamic pattern of investing, such as day trading, margin investing, stock picking, market timing, sector rotation, dollar cost averaging, technical analysis, and so forth.

To develop formal implications for trading and prices, we now specialize to the case where A represents placing a higher valuation upon speculative assets than P. Here over

[24] In the experiments of Hamill, Wilson, and Nisbett (1980), subjects were asked to rate a population (welfare recipients, or prison guards) for its characteristics after being exposed to a vivid case example involving a single member of the population. Exposure to the vivid example affected the views of subjects about the entire population even when subjects were told that the case was highly atypical of the population.

successive generations we view the assets as starting anew, so that there is no repeated learning about the prospects of a given asset. In addition, investors do not draw inferences from price when forming demand for risky assets.

4.1 Active and Passive Returns

We assume that there is a safe asset and a speculative asset, each of which generates a terminal value one period later and liquidates. The safe asset is riskfree and in zero net supply with return denoted R_F. The speculative asset S has a terminal value which is optimistically perceived by A's to have expected value $\overline{V}_A$, and by the P's to be $\overline{V}_P$, where $\overline{V}_A > \overline{V}_P$. They agree about the variance of risky asset return. We assume that a new realized terminal value is redrawn independently each period, and that investors myopically optimize each period based upon their current beliefs. We distinguish agent expectations, denoted by $E_i[]$ and 'bar' variables, from true expectations, denoted by unscripted $E[]$.

Stepping outside the model, which assumes that there is only a single security, the optimistic beliefs by the A's about the security can be viewed as reflecting a belief when there are many securities that it is possible to identify the good ones. Based on this belief, each period the A's would fix upon some security to be optimistic about. We examine a setting with many securities in Subsection 4.3.

Letting w_A and w_P be the portfolio weights chosen by each type on the speculative asset, the returns achieved by an A or a P are

$$\begin{aligned} R_A &= (1-w_A)R_F + w_A R_S \\ R_P &= (1-w_P)R_F + w_P R_S. \end{aligned} \tag{40}$$

Investors have the mean-variance optimization problem

$$\max_{w_i} \quad E_i[R_i] - \left(\frac{\nu}{2}\right) var(R_i), \quad i = A, P, \tag{41}$$

where ν is the coefficient of absolute risk aversion, and the presence of an i subscript on the expectation reflects the different beliefs of A and P about the expected value of the speculative investment. Both perceive the return variance to be σ_S^2.

Let $\bar{R}_{Si}$ denote the expectation by type i of the return on the speculative asset. Substituting for the R_A and R_P from (40) gives the optimization problems

$$\max_{w_i} \quad (1-w_i)R_F + w_i\bar{R}_{Si} - \left(\frac{\nu}{2}\right) w_i^2\sigma_S^2, \quad i = A, P. \tag{42}$$

Differentiating with respect to w_i and solving gives

$$w_i = \frac{\bar{R}_{Si} - R_F}{\nu \sigma_S^2}, \quad i = A, P. \tag{43}$$

It follows from (43) and (40) that

$$R_A - R_F = \lambda(R_P - R_F), \tag{44}$$

where

$$\lambda \equiv \frac{\bar{R}_{SA} - R_F}{\bar{R}_{SP} - R_F}. \tag{45}$$

It follows by (45) that

$$\begin{aligned} R_A &= \lambda R_P + (1-\lambda) R_F \\ &= \lambda R_P + (1-\lambda) E[R_P] - D \end{aligned} \tag{46}$$

if

$$D \equiv (1-\lambda) w_P (E[R_S] - R_F). \tag{47}$$

In (45), since A's are more optimistic than P's about the speculative asset, either $\lambda > 1$ (if its denominator is positive) or $\lambda < 0$ (if its denominator is negative). If the speculative asset is not too overpriced, it will earns a positive risk premium over the riskfree asset and will be perceived to do so by the P's, implying $\lambda > 1$. It follows that $D < 0$, a negative return penalty to active trading. Intuitively, expressing the RHS of (46) as $\lambda(R_P - E[R_P]) + E[R_P] - D$, A's earn high true expected returns relative to a mean preserving spread on R_P because such a spread leaves return constant, whereas in equilibrium A's get the benefit of some of the risk premium on investment in S. This increases the expected returns to A.

If the speculative asset is so overpriced that its expected return is below the riskfree rate, and the P's rationally perceive this to be the case, then by (45) $\lambda < 0$, so $1 - \lambda > 0$, $E[R_S] - R_F < 0$, and $w_P < 0$ by (43). Together, by (47), these imply that there is a positive return penalty to active trading, $D > 0$.

Even when $D < 0$, if A's overvalue the speculative asset and P's are rational, being an A rather than a P *decreases* the true expected utility of A's (owing to excessive risk-taking). So the return penalty to active trading D underestimates the welfare loss from active trading. Greater transaction costs of active trading (not modeled here) would also be reflected in D.

4.2 Market Equilibrium

We assume that individuals consume all their investment returns each period, at which point the assets vanish. Then each individual is newly endowed with one unit of wealth to invest. Assume the per capita supply of speculative asset is normalized to be one unit of the numeraire. Then the market clearing condition requires that

$$fw_A + (1-f)w_P = 1. \tag{48}$$

The expected return as perceived by type i is $\bar{R}_{Si} = (\overline{V}_i - p)/p$, $i = A, P$, so substituting for the w_i's from (43), and solving for the price of the speculative asset p gives

$$p = \frac{f\overline{V}_A + (1-f)\overline{V}_P}{1 + \nu\sigma_S^2 + R_F}. \tag{49}$$

By (49) and the definition of return,

$$\begin{aligned} \bar{R}_{SA} &= \overline{V}_A/p - 1 \\ &= \frac{(1-f)(\overline{V}_A - \overline{V}_P) + \overline{V}_A(\nu\sigma_S^2 + R_F)}{f\overline{V}_A + (1-f)\overline{V}_P} && (50) \\ &> R_F && (51) \end{aligned}$$

since $\overline{V}_A > f\overline{V}_A + (1-f)\overline{V}_P$.

Similar steps yield

$$\bar{R}_{SP} = \frac{f(\overline{V}_P - \overline{V}_A) + \overline{V}_P(\nu\sigma_S^2 + R_F)}{f\overline{V}_A + (1-f)\overline{V}_P}. \tag{52}$$

Since the first term in the numerator is negative and the second is positive, depending upon parameter values $\bar{R}_{SP}$ can be greater or less than 0 (or R_F). Since the passives are less optimistic, they view the speculative asset as overpriced, so they underweight it relative to the holdings of the actives, $w_P < w_A$. However, since the risky asset is in positive net supply, there is aggregate risk from holding it, so the passives may still regard it as commanding a positive expected return premium as long as the actives are not too optimistic (which would drive the price too high). Specifically, by (43) and (52), $w_P >, < 0$ are both possible.

4.3 Evolutionary Dynamics and Stable Fraction of Active Investors in Equilibrium

To derive the dynamics of the fraction of actives, we now extend the equilibrium setting to allow for many ex ante identical stocks with independent returns. These stocks are held

by even larger numbers of investors, where each investor holds only one of the stocks. As before, A and P refers to greater or lesser optimism about a given stock. The independence across stocks implies that the payoffs to the A and P strategies are independent across those investors who are trading in different stocks. In the analysis, pairs of individuals are random selected from the entire population (not just holders of a given stock). With independence across stocks, we will therefore obtain diversification across investors, so that by the law of large numbers, in the limit the system evolves deterministically. The analysis can be viewed as providing an equilibrium foundation for the partial equilibrium model of earlier sections, for the special case of the return assumptions in (13) where there is no factor risk ($\beta_A = \beta_P = 0$).

The deterministic evolution of the system will then allow us to derive the interior stable fraction of A's. This reflects a balance between two forces. On the one hand, owing to SET, the A strategy tends to spread. On the other hand, when overoptimism is prevalent, speculative securities become overpriced, and therefore will tend to generate lower returns; such returns do not attract emulation.

Specifically, we assume that there are $N = nm$ investors, m risky assets (stocks) with identical and independently distributed payoffs, and that each stock has n investors, where we will take the limit as m and n becomes large. During each time period, each investor holds only one stock, along with the riskfree asset. This assumption is made primarily for tractability, but is in the spirit of theories of limited investor information processing that result in holdings of only subsets of stocks (Merton (1987)).

In each period t, a fraction f_t of the investors in each stock hold overly optimistic belief $\bar{V}_A$ about the mean stock payoff; as before, we refer to these investors as 'active.' The rest of the investors in each stock hold the objective belief $\overline{V}$. We assume that each period investors are randomly assigned to stocks in such a way that the fraction of A investors in each stock is equal. (Since there are many investors, we ignore discreteness issues in such assignments.) These assumptions will allow us to analyze equilibrium capital market trading in each stock independently, so we omit any notation on variables to identify the specific stock. We view the risky assets as starting anew each period, so that there is no repeated learning about the prospects of a given asset.

Let the degree of optimism of a type A investor for his chosen stock be denoted by $\kappa = \overline{V}_A/\overline{V} - 1 > 0$, where κ is constant over time. We further assume, for simplicity of notation and without loss of generality, that the riskfree rate $R_F = 0$, and set the parameter a for the nonlinear term in the receiving function to zero (i.e., we eliminate the

special salience of extreme news).[25]

Since stocks payoffs are independent and the investor bases of different stocks do not overlap, at each time t the analysis of market equilibrium is, stock by stock, identical to that in Sections 4.1 and 4.2. In particular, the optimal holdings w_A, w_P, and the (objective) equilibrium expected return $E(R_S)$ all decrease with the fraction f of A investors in the population, because active (overoptimistic) investors drive up the equilibrium price, p, of each stock:

$$p_t = \left(\frac{1+f_t\kappa}{1+\nu\sigma_S^2}\right)\overline{V} \tag{53}$$

$$E_t(R_S) = \frac{\nu\sigma_S^2 - f_t\kappa}{1+f_t\kappa} \tag{54}$$

$$w_A(t) = \frac{(1+\kappa)\nu\sigma_S^2 + (1-f_t)\kappa}{(1+f_t\kappa)\nu\sigma_S^2} \tag{55}$$

$$w_P(t) = \frac{\nu\sigma_S^2 - f_t\kappa}{(1+f_t\kappa)\nu\sigma_S^2}. \tag{56}$$

We continue to omit subscripts denoting individual stocks, because all stocks are identical and thus the quantities above are the same for all stocks.

Each period, we assume that a fraction θ of the investors are randomly selected to meet in pairs without regard to type or to which stocks they are holding. When N is large, there is a probability of almost exactly $2f(1-f)$ of a mixed pair so that one is A and the other is P, and almost surely they hold different stocks. In the next period, someone who is converted to A becomes optimistic about whatever stock he is assigned to, and someone who becomes converted to P acquires objective beliefs about whatever stock he is assigned to.

So during a given period $[t, t+1]$, there are θN meetings of pairs of individuals. Let the meetings be indexed by ω, and let ζ denote the function that specifies which stocks are held by each individual in a specific mixed meeting, as a function of the pairing and each investor's type. For a given meeting ω between an A holding stock $\zeta_{A\omega}$ and a P holding stock $\zeta_{P\omega}$, their returns are given by

$$R_{A\omega} = w_A(t)R_{S\zeta_{A\omega}}, \quad R_{P\omega} = w_P(t)R_{S\zeta_{P\omega}}. \tag{57}$$

We assume that the sending and receiving functions are as in Section 2. So after θN meetings of pairs during a given period $[t, t+1]$, the change in the population frequency of

[25] The parameter a was only needed for the model's skewness predictions, but the return distributions in this section are all Gaussian. Allowing for $a > 0$ makes expressions more cumbersome but does not add any insights. We have verified that Proposition 4 still holds when $a > 0$.

A is (up to a stochastic error that shrinks with N)

$$\begin{aligned} f_{t+1} - f_t &= \left(\frac{\chi}{2N}\right) \sum_{\omega=1}^{\theta N} [T_{AP}(R_{A\omega})] - [T_{PA}(R_{P\omega})] \\ &= \left(\frac{\chi}{2N}\right) \sum_{\omega=1}^{\theta N} B\left(R_{A\omega}^2 - R_{P\omega}^2\right) + C(R_{A\omega} - R_{P\omega}), \end{aligned}$$

where parameters $B = b\beta$ and $C = b\gamma + c\beta$. Substituting equations (55), (56), and (57) into the above, we have

$$f_{t+\Delta} - f_t = \left(\frac{\chi}{2}\right) \frac{1}{N} \sum_{\omega=1}^{\theta N} B[w_A(t)^2 R_{S\zeta_{A\omega}}^2 - w_P(t)^2 R_{S\zeta_{P\omega}}^2] + C[w_A(t) R_{S\zeta_{A\omega}} - w_P(t) R_{S\zeta_{P\omega}}]$$

We let n and m (and hence the population size $N = nm$) approach infinity to obtain a deterministic dynamic for the fraction of actives. Since stock returns are identical and independently distributed, we can apply the law of large numbers to the summation on the RHS of the last equation above, replacing each term being averaged with its expectation. This results in the following expression for the dynamic of the population frequency of A:

$$\frac{f_{t+1} - f_t}{f_t(1 - f_t)} = \theta[w_A(t) - w_P(t)]\{B[w_A(t) + w_P(t)][E_t(R_S)^2 + \sigma_S^2] + CE_t(R_S)\}, \quad (58)$$

where $E_t(R_S)$ is given in equation (56), and $w_A(t) - w_P(t)$ and $w_A(t) + w_P(t)$ can be expressed as functions of f_t,

$$w_A(t) - w_P(t) = \frac{\kappa(1 + \nu\sigma_S^2)}{(1 + f_t\kappa)\nu\sigma_S^2} \quad (59)$$

$$w_A(t) + w_P(t) = \frac{(2 + \kappa)\nu\sigma_S^2 + (1 - 2f_t)\kappa}{(1 + f_t\kappa)\nu\sigma_S^2}. \quad (60)$$

By (58), the net conversion rate from P to A, $(f_{t+1} - f_t)/f_t$, is a decreasing function of f_t. Specifically, it is the product of $1 - f_t$ and the right hand side of (58), which is a decreasing function of f_t, since $w_A(t) - w_P(t)$, $w_A(t) + w_P(t)$ and $E_t(R_S)$ all decrease with f_t.

When f is small, the stocks have positive expected return premia, which means that strategy A earns high expected returns relative to P, i.e., $D < 0$.[26] In this circumstance, other investors tend to convert to A (becoming optimistic) as they hear about the high returns being experienced using A. However, as the fraction of A's becomes sufficiently

[26] If $E[R_S] - R_F > 0$, then $w_P > 0$ and $\lambda = w_A/w_P > 1$, and $D \equiv (1 - \lambda)w_P(E[R_S] - R_F) < 0$.

large, the expected return premium on the speculative asset declines or even turns negative. This decline limits the spread of active investing through the population.

So long as the optimistic belief is not too extreme (more precisely, if $\kappa < \nu\sigma_S^2$), $E(R_S)$ is positive, and so is the right hand side of (58), regardless of the value of f (f is bounded between 0 and 1). Thus the fraction of A increases indefinitely, and type A dominates the population.

However, if the A's have sufficiently optimistic beliefs ($\kappa > \nu\sigma_S^2$), as f grows the speculative assets become highly overpriced, driving $E(R_S)$ negative. This results in an expected return penalty to A. As the actual and reported returns on A diminish, so does the net conversion rate from P to A, which becomes negative when the fraction f of active investors becomes too large.

Thus, when the A belief is sufficiently optimistic, there exists a *stable fraction* $f^* \in (0,1)$ of type A such that the net conversion rate from P to A is zero starting at f^* fraction of actives. The fraction f^* is stable in the sense that $\Delta f > 0$ for $f < f^*$, and $\Delta f < 0$ for $f > f^*$.

By equation (58) and the fact that $w_A(t) - w_P(t)$ given in (59) is always positive, the stable fraction f^* satisfies $H(f^*) = 0$, where

$$H(f) \equiv B[w_A(t) + w_P(t)][E_t(R_S)^2 + \sigma_S^2] + CE_t(R_S). \tag{61}$$

Substituting equations (54), (55) and (56) into the above, $H(f^*) = 0$ can be equivalently written as $G(f^*) = 0$, where

$$G(f) \equiv B[(2+\kappa)\nu\sigma_S^2+(1-2f)\kappa][(\nu\sigma_S^2-f\kappa)^2+\sigma_S^2(1+f\kappa)^2]+C\nu\sigma_S^2(1+f\kappa)^2(\nu\sigma_S^2-f\kappa). \tag{62}$$

Given the model parameters, G is a cubic polynomial in f, with $G(0) > 0$. When the A's have sufficiently optimistic beliefs, i.e., when $\kappa > \nu\sigma_S^2$ is sufficiently large, $G(1) < 0$, and the discriminant of G is negative. Hence there exists a unique $f^* \in (0,1)$ satisfying $G(f^*) = 0$.

The expected return premium on the risky assets corresponding to the stable fraction f^* must be negative, because the net conversion from P to A is still positive when $E(R_S) = 0$. Intuitively, SET would cause conversion to A until everyone adopts A, unless A has an offsetting adverse effect on expected returns that opposes such conversion. We summarize the above results in the following proposition.

Proposition 4 *If the type A investors are sufficiently optimistic, then there exists a stable fraction $f^* \in (0,1)$, such that $\Delta f > 0$ for $f < f^*$, and $\Delta f < 0$ for $f > f^*$. Corresponding to f^*, the expected return premium on the speculative asset is negative.*

Given that the stable fraction f^* of A satisfies $H(f^*) = 0$, we can study how f^* varies with key model parameters. Using (61), it is straightforward to verify that

$$\frac{\partial H}{\partial f} < 0, \ \frac{\partial H}{\partial \kappa} < 0, \ \frac{\partial H}{\partial c} < 0, \ \frac{\partial H}{\partial \gamma} < 0. \tag{63}$$

The first two inequalities in (63) derive from the fact that $E(R_S)$ decreases with the fraction of actives and with their optimism κ. The greater the fraction of actives, or the more optimistic they are about stock payoffs, the more that stocks are overpriced. The last two inequalities in (63) result from the fact that the expected return on the speculative asset is negative at the stable fraction of actives.

Applying the implicit function theorem to $H(f^*) = 0$ using (64) and the inequalities in (63) gives

$$\frac{\partial f^*}{\partial \kappa} < 0, \ \frac{\partial f^*}{\partial c} < 0, \ \frac{\partial f^*}{\partial \gamma} < 0. \tag{64}$$

We therefore have:

Proposition 5 *If the type A investors are sufficiently optimistic, the stable fraction f^* of A decreases with the degree of optimism κ, the sender conversability γ, and the receiver susceptibility c.*

Intuitively greater susceptibility c helps transform the receiver only if the sender actually sends. In equilibrium A earns lower expected returns than P; owing to SET, this reduces the sending probability by type A relative to P.

Since in equilibrium A earns lower expected returns than P, greater conversability γ causes greater spread of bad news about A rather than P. This results in a lower stable frequency of A.

Although phrased differently, these findings are consistent with the partial equilibrium comparative statics findings of Proposition 2 Parts 11 and 12. These provided conditions under which the frequency of A was *increasing* with γ and c. However, the condition for the increasing direction in Parts 11 and 12 is that A earn sufficiently high expected returns compared to P. Here A earns lower expected returns than P, which, intuitively, leads to an opposing effect.

For Proposition 2 Part 11, the conclusion of a positive effect of conversability on f does not actually require that A earn a higher expected return than P, because $a > 0$ contributes positively (see equation 33). Since we have set $a = 0$ in the equilibrium analysis, we have eliminated this effect.

As for other parameters, intuitively, greater sensitivity b of receivers to returns tends to promote A by magnifying the effect of SET (reflected in β), which is biased in favor of A since A generates the extreme high returns that SET can operate on. This is the effect emphasized in Part 10 of Proposition 2. The opposing effect is that A earns lower returns on average, which discourages emulation, and greater sensitivity of receivers magnifies this effect as well.

Greater self-enhancing transmission bias, as reflected in the β parameter, tends to increase the evolution toward A because SET causes greater reporting of the high returns that make A enticing for receivers. However, A's earns lower returns on average, which, owing to SET, implies that A's report returns less often. So to the extent that receivers have an inherent susceptibility to be converted regardless of the level of the return (i.e., $c > 0$), this effect opposes the basic effect.

4.4 Trading Volume

We now generalize the previous model to provide implications for volume of trade, by allowing differences in optimism about the risky asset among A investors. We develop our conjectures heuristically here. One interpretation of A versus P that we have considered previously is that the A's are unduly optimistic about a given risky security, whereas the P's are not. An alternative interpretation which we focus on in this subsection is that A has a more general belief about whether stock picking or market timing are worthwhile activities. Investors who do believe that these are worthwhile will conduct fundamental and technical analyses which provide them with what they perceive to be signals about the value of the risky asset. This can be contrasted with passive investors who (by assumption) share some common prior belief (some conventional view prevalent in society), do not investigate further, and hence remain in agreement. In consequence, actives form divergent beliefs about the asset whereas passive investors do not.

We therefore allow the A's to have heterogeneous expectations about the value of the speculative asset,

$$\overline{V}^{Ak} = \overline{V}^{A} + \psi^{k}, \tag{65}$$

where k refers to an individual type A investor, $\overline{V}^{Ak}$ is the expectation of investor k of the terminal cash flow of the security, ψ^k is uniformly distributed on an interval $[-u, u]$ which is centered at zero. The parameter u captures the amount of disagreement among the A's.

Owing to the diversity of perceptions among the A's, they trade with each other. This results in an increase in volume of trade as A increases in frequency in the population. Ow-

ing to the difference in belief between A's and P's, there is also trading between individuals of different types.

The diversity of the A's makes the analysis of evolution of the population more complex. However, if all we are concerned about is directional predictions about volume, we can let u approach zero. In that case the evolution of the fractions of A's is arbitrarily well approximated by the fractions in a setting where the A's are identical. We additionally assume that the difference in beliefs of the A's and P's become arbitrarily close to zero more rapidly than u (i.e., $(\overline{V}_A - \overline{V}_P)/u) \to 0$). This assumption captures the idea that there is more dispersion in beliefs among the actives than the difference between the average belief of the A's and that of P's. Under this assumption, volume is dominated by trading amongst A's rather than between A's and P's. As a result, as the frequencies of the different types shift, the qualitative prediction that volume of trade increases with the fraction of A's remains valid.

More generally, if the assumptions about belief differences do not hold the effect described here still applies, but could potentially be outweighed by another effect, that as the fraction of A's rises too high, there will be diminished trade between the A's and the P's. A more general sufficient condition is that the A's be sufficiently active in the sense that their idiosyncratic beliefs be sufficiently extreme that trading between them is more important than trading between the A's and the P's.

Thus, the comparative statics predictions from Proposition 2 about the conditions under which the expected fraction of A's grows also provide predictions about what determines increased trading volume. Similarly, the earlier analysis of local bias in investment also implies greater trading of stocks that are geographically local or otherwise familiar to investors.

As discussed in Subsection 2.3, the model implies a frothy churning of beliefs as investing ideas are transmitted from person to person. Even if A does not end up dominating the population, stochastic fluctuation in population fractions of A and P is a continuing source of turnover. In consequence, the model implies excessive volume of trade even in the absence of overconfidence, and that such volume is increasing with proxies for social connectedness.

5 Concluding Remarks

Individual investors often invest actively and thereby earn lower expected returns and bear higher risk. Social interaction seems to exacerbate the bias toward active trading. In the model presented here, biases in the social transmission of behaviors favor active over passive

trading strategies.

We argue that it is important to understand the spread of investment ideas as arising from sender and receiver functions. This allows separate analysis of the factors that cause an individual to talk about an investment idea, versus making an individual receptive to such an idea upon hearing about it. In the model, senders' propensity to communicate their returns to receivers, and receivers' propensity to be converted, are increasing in sender return. Receivers' propensity to attend to and be converted by the sender is increasing and convex in sender return.

Owing both to the multiplicative effect of these increasing functions, and the convexity of the receiving function, the rate of conversion of investors to active investing is convex in sender return. Unconditionally, active strategies (high variance, skewness, and personal involvement) dominate the population unless the mean return penalty to active investing is too large. Thus, the model can explain overvaluation of 'active' asset characteristics even if investors have no inherent preference over them. The model also can explain local bias in investment, and offers implications about how social interaction affects volume of trade.

Conversations are influenced by chance circumstances, subtle cues, and even trifling costs and benefits to the transactors. This suggests that small variations in social environment can have large effects on economic outcomes. For example, the model suggests that a shift in the social acceptability of talking about one's successes or of discussing personal investments more generally could have large effects on the amount of risk taking and active investing in the social and market equilibrium. It would be interesting to model feedback from the frequency of active investors to the acceptability of discussing one's investment successes, which could result in multiple equilibria with different amounts of active investing.

The model helps explain several empirical puzzles about investor trading and asset pricing, and offers other new implications. Much of the empirical literature on social interaction in investment focuses on *whether* information or behaviors are transmitted, and perhaps on what affects the strength of social contagion. Our approach suggests that it is also valuable to test for how *biases in the transmission process* affect the relative success of different kinds of behaviors.

More broadly, the approach offered here illustrates the possible benefits to considering cultural evolution as an explanation for stylized facts about investing and pricing. It would be interesting to extend the approach to study the determinants of the popularity of different money money management vehicles, such as mutual funds, ETFs, and hedge funds. Our approach also offers a micro-foundation for research on the spread of investor

sentiment across investors. The social contagion of investment ideas also seems important for the process by which bubbles form. For example, the millennial high-tech stock market boom coincided with the rise of investment clubs and chat rooms. The cultural evolutionary approach offers a possible framework for modeling how investment ideas cause bubbles and crashes.

References

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2006, February). The cross-section of volatility and expected returns. *Journal of Finance 61*(1), 259–299.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2009, January). High idiosyncratic volatility and low returns: International and further U.S. evidence. *Journal of Financial Economics 91*(1), 1–23.

Arkes, H. R., L. Boehm, and G. Xu (1991). Determinant of judged validity. *Journal of Experimental Social Psychology 27*(6), 576–605.

Arkes, H. R., C. Hackett, and L. Boehm (1989, April/June). The generality of the relation between familiarity and judged validity. *Journal of Behavioral Decision Making 2*(2), 81–94.

Bacon, F. T. (1979, May). Credibility of repeated statements: Memory for trivia. *Journal of Experimental Psychology: Human Learning and Memory 5*(3), 241–52.

Baker, M. P., B. Bradley, and J. Wurgler (2010, March). Benchmarks as limits to arbitrage: Understanding the low volatility anomaly. Working paper, Harvard Business School, NYU Working Paper No. FIN-10-002.

Bali, T. G., N. Cakici, and R. Whitelaw (2009, February). Maxing out: Stocks as lotteries and the cross-section of expected returns. NYU Working Paper No. FIN-08-025.

Banerjee, A. (1992, September). A simple model of herd behavior. *Quarterly Journal of Economics 107*(3), 797–817.

Banerjee, A. and D. Fudenberg (2004, January). Word-of-mouth learning. *Games and Economic Behavior 46*(1), 1–22.

Barber, B., C. Heath, and T. Odean (2003, December). Good reasons sell: Reason-based choice among individual investors in the stock market. *Management Science 49*(12), 1636–1652.

Barber, B., Y.-T. Lee, Y.-J. Liu, and T. Odean (2009). Just how much do individual investors lose by trading? *Review of Financial Studies 22*(2), 609–632.

Barber, B. and T. Odean (2000a, January/February). Too many cooks spoil the profits: The performance of investment clubs. *Financial Analyst Journal 56*(1), 17–25.

Barber, B. and T. Odean (2000b, April). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance 55*(2), 773–806.

Barber, B. and T. Odean (2002, March). Online investors: Do the slow die first? *Review of Financial Studies 15*(2), 455–488.

Barber, B. and T. Odean (2008, April). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies 21*(2), 785–818.

Barberis, N. and M. Huang (2008, December). Stocks as lotteries: The implications of probability weighting for security prices. *American Economic Review 95*(5), 2066–2100.

Barberis, N. and W. Xiong (2010, July). Realization utility. Working Paper, Yale School of Management.

Bem, D. J. (1972). Self-perception theory. In L. Berkowitz (Ed.), *Advances in Experimental Social Psychology*, Volume 6, pp. 1–62. New York: Academic Press.

Benabou, R. and J. Tirole (2002, August). Self-confidence and personal motivation. *Quarterly Journal of Economics 117*(3), 871–915.

Benartzi, S. (2001). Excessive extrapolation and the allocation of 401(k) accounts to company stock. *Journal of Finance 56*(5), 1747–1764.

Bikhchandani, S., D. Hirshleifer, and I. Welch (1992, October). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy 100*(5), 992–1026.

Bisin, A. and T. Verdier (2000). Beyond the melting pot: Cultural transmission, marriage, and the evolution of ethnic and religious traits. *Quarterly Journal of Economics 115*(3), 955–988.

Bisin, A. and T. Verdier (2001, April). The economics of cultural transmission and the evolution of preferences. *Journal of Economic Theory 97*(2), 298–319.

Borgida, E. and R. E. Nisbett (1977, September). The differential impact of abstract vs. concrete information on decisions. *Journal of Applied Social Psychology 7*(3), 258–271.

Bornstein, R. and P. D'Agostino (1992). Stimulus recognition and the mere exposure effect. *Journal of Personality and Social Psychology 63*(4), 545–552.

Boyer, B., T. Mitton, and K. Vorkink (2010, January). Expected idiosyncratic skewness. *Review of Financial Studies 23*(1), 169–202.

Boyer, B. H. and K. Vorkink (2011, July). Stock options as lotteries. Working Paper, Brigham Young University.

Brenner, L. A., D. J. Koehler, and A. Tversky (1996). On the evaluation of one-sided evidence. *Journal of Behavioral Decision Making 9*, 59–70.

Brown, J. R., Z. Ivkovich, P. A. Smith, and S. Weisbenner (2008, June). Neighbors matter: Causal community effects and stock market participation. *Journal of Finance 63*(3), 1509–1531.

Brunnermeier, M. (2001). *Asset Pricing under Asymmetric Information: Bubbles, Crashes, Technical Analysis and Herding*. Oxford, UK: Oxford University Press.

Brunnermeier, M. K. and J. Parker (2005, September). Optimal expectations. *American Economic Review 95*(4), 1092–1118.

Calvet, L. E., J. Y. Campbell, and P. Sodini (2007, October). Down or out: Assessing the welfare costs of household investment mistakes. *Journal of Political Economy 115*(5), 707–747.

Campbell, J. Y., J. D. Hilscher, and J. Szilagyi (2008, December). In search of distress risk. *Journal of Finance 63*(6), 2899–2939.

Carhart, M. M. (1997, March). On persistence in mutual fund performance. *Journal of Finance 52*(1), 57–82.

Case, K. E. and R. J. Shiller (1988, November/December). The behavior of home buyers in boom and post-boom markets. *New England Economic Review 80*(3), 29–46.

Chancellor, E. (2000, June). *Devil Take the Hindmost: A History of Financial Speculation*. NY, USA: Penguin Group.

Choi, J. J., D. Laibson, and B. C. Madrian (2010, April). Why does the law of one price fail? An experiment on index mutual funds. *Review of Financial Studies 23*(4), 1405–1432.

Cialdini, R. B. and N. J. Goldstein (2004, February). Social influence: Compliance and conformity. *Annual Review of Psychology 55*, 591–621.

Cipriani, M. and A. Guarino (2002). Social learning and financial crises. In *Risk measurement and systemic risk: Proceedings of the third joint Central Bank research conference*, pp. 77–83. Basel, Switzerland: The Committee on the Global Financial System, Bank for International Settlements Press.

Cipriani, M. and A. Guarino (2008, April). Herd behavior and contagion in financial markets. *B.E. Journal of Theoretical Economics 8*(1), Article 24.

Cohen, L., A. Frazzini, and C. J. Malloy (2008, October). The small world of investing: Board connections and mutual fund returns. *Journal of Political Economy 116*(5), 951–979.

Cohen, L., A. Frazzini, and C. J. Malloy (2010, August). Sell-side school ties. *Journal of Finance 65*(4), 1409–1437.

Conrad, J. S., R. F. Dittmar, and E. Ghysels (2009, December). Ex ante skewness and expected stock returns. Working paper, University of North Carolina at Chapel Hill.

Dahlquist, M., J. V. Martinez, and P. Söderlind (2011, December). Individual investor activity and performance. Working Paper, Stockholm School of Economics.

Daniel, K. D., M. Grinblatt, S. Titman, and R. Wermers (1997, July). Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance 52*(3), 1035–1058.

Daniel, K. D., D. Hirshleifer, and S. H. Teoh (2002, January). Investor psychology in capital markets: Evidence and policy implications. *Journal of Monetary Economics 49*(1), 139–209.

Dawkins, R. (1976). *The Selfish Gene*. New York: Oxford University Press.

DeBondt, W. F. M. (1993). Betting on trends: Intuitive forecasts of financial risk and return. *International Journal of Forecasting 9*, 355–371.

DeBondt, W. F. M. and R. H. Thaler (1995). Financial decision-making in markets and firms: A behavioral perspective. In R. A. Jarrow, V. Maksimovic, and W. T.

Ziemba (Eds.), *Finance, Handbooks in Operations Research and Management Science*, Volume 9, Chapter 13, pp. 385–410. Amsterdam: North Holland.

DeMarzo, P., D. Vayanos, and J. Zwiebel (2001). Social networks and financial markets. Working paper, MIT and Stanford University.

DeMarzo, P., D. Vayanos, and J. Zwiebel (2003). Persuasion bias, social influence, and uni-dimensional opinions. *Quarterly Journal of Economics 118*, 909–968.

Devenow, A. and I. Welch (1996, April). Rational herding in financial economics. *European Economic Review 40*(3-5), 603–615.

Dichev, I. D. and G. Yu (2011, May). Higher risk, lower returns: What hedge fund investors really earn. *Journal of Financial Economics 100*(2), 248–263.

Dodds, P. S. and D. J. Watts (2005, February). A generalized model of social and biological contagion. *Journal of Theoretical Biology 232*(4), 587–604.

Duflo, E. and E. Saez (2002, July). Participation and investment decisions in a retirement plan: The influence of colleagues' choices. *Journal of Public Economics 85*(1), 121–148.

Duflo, E. and E. Saez (2003, August). The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment. *Quarterly Journal of Economics 118*, 815–842.

East, R., K. Hammond, and M. Wright (2007, June). The relative incidence of positive and negative word of mouth: A multi-category study. *International Journal of Research in Marketing 24*(2), 175–184.

Ederington, L. H. and E. V. Golubeva (2010, March). The impact of risk and return perceptions on the portfolio reallocation decisions of mutual fund investors. Working Paper, University of Oklahoma.

Eleswarapu, V. (2004, November). Demography and intensity of stock trading: The effect of social interaction. Working paper, Cox School of Business, Southern Methodist University.

Ellison, G. and D. Fudenberg (1995, February). Word-of-mouth communication and social learning. *Quarterly Journal of Economics 110*(1), 93–125.

Engelberg, J., C. Sasseville, and J. Williams (2009, December). Market madness? The case of Mad Money. Working Paper, UNC Kenan-Flagler Business School.

Eraker, B. and M. J. Ready (2010, December). Do investors overpay for stocks with lottery-like payoffs? An examination of the returns on OTC stocks. Working Paper, University of Wisconsin - Madison.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics 33*, 3–56.

Fang, L. and J. Peress (2009, October). Media coverage and the cross-section of stock returns. *Journal of Finance 64*(5), 2023–2052.

Fast, N. J., C. Heath, and G. Wu (2009, July). Common ground and cultural prominence: How conversation reinforces culture. *Psychological Science 20*(7), 904–911.

Fiedler, K. (2008, January). The ultimate sampling dilemma in experience-based decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition 34*(1), 186–203.

Fiske, S. T. (1980, June). Attention and weight in person perception: The impact of negative and extreme behavior. *Journal of Personality and Social Psychology 38*(6), 889–906.

French, K. R. (2008, August). Presidential address: The cost of active investing. *Journal of Finance 63*(4), 1537–1573.

Georgarakos, D. and G. Pasini (2011, October). Trust, sociability, and stock market participation. *Review of Finance 15*(4), 693–725.

Gigerenzer, G. (1984, Summer). External validity of laboratory experiments: The frequency-validity relationship. *American Journal of Psychology 97*(2), 185–195.

Goetzmann, W. N. and A. Kumar (2008). Equity portfolio diversification. *Review of Finance 12*(3), 433–463.

Goffman, E. (1961). *Encounters*. Indianapolis, IN: Bobbs-Merrill.

Gray, W. R. (2009, December). Do hedge fund managers identify and share profitable ideas? Working paper, Empirical Finance, LLC, University of Chicago.

Green, T. C. and B.-H. Hwang (2010, April). IPOs as lotteries: Skewness preference and first-day returns. Working paper, Emory University-Goizueta Business School.

Greenwald, A. G. (1980). The totalitarian ego: Fabrication and revision of personal history. *American Psychologist 35*(7), 603–618.

Greenwood, R. and S. Nagel (2009, August). Inexperienced investors and bubbles. *Journal of Financial Economics 93*(2), 239–258.

Griffin, J. M., F. Nardari, and R. M. Stulz (2007, May). Do investors trade more when stocks have performed well? Evidence from 46 countries. *Review of Financial Studies 20*(3), 905–951.

Griliches, Z. (1957, October). Hybrid corn: An exploration in the economics of technological change. *Econometrica 25*(4), 501–522.

Hamill, R., T. D. Wilson, and R. E. Nisbett (1980, April). Insensitivity to sample bias: Generalizing from atypical cases. *Journal of Personality and Social Psychology 39*(4), 578–589.

Hasher, L., D. Goldstein, and T. Toppino (1977, February). Frequency and the conference of referential validity. *Journal of Verbal Learning and Verbal Behavior 16*(1), 107–112.

Hawkins, S. A. and S. J. Hoch (1992, September). Low-involvement learning: Memory without evaluation. *Journal of Consumer Research 19*(2), 212–225.

Healy, A. F. (1981, September). The effects of visual similarity on proofreading for misspellings. *Memory and Cognition 9*(5), 453–460.

Hearst, E. (1991). Psychology and nothing. *American Scientist 79*(5), 432–443.

Henrich, J. (2001). Cultural transmission and the diffusion of innovations: Adoption dynamics indicate that biased cultural transmission is the predominate force in behavioral change and much of sociocultural evolution. *American Anthropologist 103*, 992–1013.

Henrich, J. and R. Boyd (1998). The evolution of conformist transmission and the emergence of between-group differences. *Evolution and Human Behavior 19*, 215–242.

Hirshleifer, D. and S. H. Teoh (2003, March). Herd behavior and cascading in capital markets: A review and synthesis. *European Financial Management 9*(1), 25–66.

Hirshleifer, D. and S. H. Teoh (2009). Thought and behavior contagion in capital markets. In T. Hens and K. Schenk-Hoppe (Eds.), *Handbook Of Financial Markets: Dynamics And Evolution*, Handbooks in Finance, Chapter 1, pp. 1–46. Amsterdam, The Netherlands: North-Holland.

Holtgraves, T. and T. K. Srull (1989, September). The effects of positive self-descriptions on impressions. *Personality and Social Psychology Bulletin 15*(3), 452–462.

Hong, H., J. Kubik, and J. C. Stein (2004, February). Social interactions and stock market participation. *Journal of Finance 59*(1), 137–163.

Hong, H., J. Kubik, and J. C. Stein (2005, December). Thy neighbor's portfolio: Word-of-mouth effects in the holdings and trades of money managers. *Journal of Finance 60*(6), 2801–2824.

Huang, W., Q. Liu, S. G. Rhee, and L. Zhang (2010). Return reversals, idiosyncratic risk, and expected returns. *Review of Financial Studies 23*(1), 147–168.

Huberman, G. (2001). Familiarity breeds investment. *Review of Financial Studies 14*(3), 659–680.

Ivkovich, Z. and S. Weisbenner (2007, July). Information diffusion effects in individual investors' common stock purchases: Covet thy neighbors' investment choices. *Review of Financial Studies 20*(4), 1327–1357.

Jackson, M. O. (2008). *Social and Economic Networks*. Princeton, NJ: Princeton University Press.

Jiang, G. J., D. Xu, and T. Yao (2009). The information content of idiosyncratic volatility. *Journal of Financial and Quantitative Analysis 44*(1), 1 – 28.

Kahneman, D. and S. Frederick (2002). Representativeness revisited: Attribute substitution in intuitive judgment. In T. Gilovich, D. Griffin, and D. Kahneman (Eds.), *Heuristics and Biases: The Psychology of Intuitive Judgment*, pp. 49–81. New York: Cambridge University Press.

Kallick, M., D. Smits, T. Dielman, and J. Hybels (1979). A survey of American gambling attitudes and behavior. Research Report Series, Survey Research Center, Institute for Social Research, University of Michigan.

Karlsson, N., G. F. Loewenstein, and D. J. Seppi (2009, February). The 'Ostrich Effect': Selective attention to information. *Journal of Risk and Uncertainty 38*(2), 95–115.

Kaustia, M. and S. Knüpfer (2010, February). Peer performance and stock market entry. Working paper, AFA 2010 Atlanta Meetings.

Kelly, M. and C. O. O'Grada (2000). Market contagion: Evidence from the panics of 1854 and 1857. *American Economic Review 90*(5), 1110–1124.

Koehler, J. J. and M. Mercer (2009). Selection neglect in mutual fund advertisements. *Management Science 55*(7), 1107–1121.

Kumar, A. (2009, April). Who gambles in the stock market? *Journal of Finance 64*(4), 1889–1933.

Kunda, Z. (1990, May). The case for motivated reasoning. *Psychological Bulletin 108*(3), 480–498.

Lachlan, R. F., L. Crooks, and K. N. Laland (1998, July). Who follows whom? Shoaling preferences and social learning of foraging information in guppies. *Animal Behavior 56*(1), 181–190.

Langer, E. J. and J. Roth (1975). Heads I win tails it's chance: The illusion of control as a function of the sequence of outcomes in a purely chance task. *Journal of Personality and Social Psychology 32*, 951–955.

Leary, M. R. (1996). *Self presentation: Impression management and interpersonal behavior*. Boulder, Colorado: Westview Press.

Leary, M. R. and R. M. Kowalski (1990, January). Impression management: A literature review and two-component model. *Psychological Bulletin 107*(1), 34–47.

Loughran, T. and J. Ritter (1995, March). The new issues puzzle. *Journal of Finance 50*(1), 23–52.

Lu, T. J. (2011, April). Social interaction effects and individual portfolio choice: Evidence from 401(k) pension plan investors. Working Paper, Wharton School, University of Pennsylvania.

Massa, M. and A. Simonov (2005, February). History versus Geography: The role of college interaction in portfolio choice. CEPR Discussion Paper No. 4815.

Merton, R. C. (1987, July). A simple model of capital market equilibrium with incomplete information. *Journal of Finance 42*(3), 483–510.

Mitton, T. and K. Vorkink (2007). Equilibrium underdiversification and the preference for skewness. *Review of Financial Studies 20*(4), 1255–1288.

Moran, P. A. P. (1962). *The Statistical Processes of Evolutionary Theory*. New York: Oxford University Press.

Moreland, R. L. and R. Beach (1992). Exposure effects in the classroom: The development of affinity among students. *Journal of Experimental Social Psychology 28*, 255–276.

Morris, S. (2000, January). Contagion. *Review of Economic Studies 67*(1), 57–78.

Moskowitz, G. B. (2004). *Social Cognition: Understanding Self and Others*. New York, NY: The Guilford Press.

Neisser, U. (1963, September). Decision-time without reaction-time: Experiments in visual scanning. *American Journal of Psychology 76*(3), 376–385.

Nisbett, R. and L. Ross (1980). *Human Inference: Strategies and Shortcomings of Social Judgment*. Englewood Cliffs, NJ: Prentice-Hall.

Nisbett, R. E. and E. Borgida (1975, May). Attribution and the psychology of prediction. *Journal of Personality and Social Psychology 32*(5), 932–943.

Nisbett, R. E., D. H. Krantz, C. Jepson, and Z. Kunda (1983, October). The use of statistical heuristics in everyday inductive reasoning. *Psychological Review 90*(4), 339–363.

Ozsoylev, H. N. and J. Walden (2011, November). Asset pricing in large information networks. *Journal of Economic Theory 146*(6), 2252–2280.

Parlour, C. A., V. Prasnikar, and U. Rajan (2007, August). Compensating for the winner's curse: Experimental evidence. *Games and Economic Behavior 60*(2), 339–356.

Parsons, C. A. and J. Engelberg (2009, August). Isolating media effects in financial markets. University of North Carolina at Chapel Hill Working Paper.

Ross, L. D., T. M. Amabile, and J. L. Steinmetz (1977, July). Social roles, social control, and biases in social-perception. *Journal of Personality and Social Psychology 35*(7), 485–94.

Sandholm, W. H. (2010). *Population Games and Evolutionary Dynamics*. MIT Press.

Scharfstein, D. S. and J. C. Stein (1990). Herd behavior and investment. *American Economic Review 80*, 465–479.

Schlenker, B. R. (1980). *Impression Management: The Self–Concept, Social Identity, and Interpersonal Relations*. Monterey, CA: Brooks/Cole Publishing Company.

Schwartz, M. (1982). Repetition and rated truth value of statements. *American Journal of Psychology 95*(3), 393–407.

Shiller, R. J. (1989). *Market Volatility*. Cambridge: MIT Press.

Shiller, R. J. (1990). Speculative prices and popular models. *Journal of Economic Perspectives 4*(2), 55–65.

Shiller, R. J. (2000a). Conversation, information, and herd behavior. *American Economic Review 85*(2), 181–185.

Shiller, R. J. (2000b). *Irrational exuberance*. Princeton, N.J.: Princeton University Press.

Shiller, R. J. and J. Pound (1989). Survey evidence on the diffusion of interest and information among investors. *Journal of Economic Behavior and Organization 12*(1), 46–66.

Shive, S. (2010, February). An epidemic model of investor behavior. *Journal of Financial and Quantitative Analysis 45*(1), 169–198.

Sirri, E. R. and P. Tufano (1998, October). Costly search and mutual fund flows. *Journal of Finance 53*(5), 1589–1622.

Smith, V. L., G. L. Suchanek, and A. W. Williams (1988, September). Bubbles, crashes and endogenous expectations in experimental spot asset markets. *Econometrica 56*(5), 1119–1151.

Stasser, G., L. A. Taylor, and C. Hanna (1989, July). Information sampling in structured and unstructured discussions of three- and six-person groups. *Journal of Personality and Social Psychology 57*(1), 67–78.

Stasser, G. and W. Titus (1985). Pooling of unshared information in group decision making: Biased information sampling during discussion. *Journal of Personality and Social Psychology 48*, 1467–1478.

Statman, M., S. Thorley, and K. Vorkink (2006). Investor overconfidence and trading volume. *Review of Financial Studies 19*(4), 1531–1565.

Teoh, S. H. and Y. Zhang (2012). Idiosyncratic risk and the cross–section of expected stock returns. *Accounting Review*.

Tesar, L. and I. M. Werner (1995). Home bias and high turnover. *Journal of International Money and Finance 14*(4), 467–492.

Tetlock, P. C. (2007, 06). Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance 62*(3), 1139–1168.

Tversky, A. and D. Kahneman (1971). Belief in the law of small numbers. *Psychological Bulletin 76*(2), 105–110.

Tversky, A. and D. Kahneman (1974, September). Judgment under uncertainty: Heuristics and biases. *Science 185*(4157), 1124–1131.

Vissing-Jorgensen, A. (2003). Perspectives on behavioral finance: Does "irrationality" disappear with wealth? Evidence from expectations and actions. *NBER Macroeconomics Annual 2003 18*, 139–194.

von Hippel, W. and R. Trivers (2011, February). The evolution and psychology of self-deception. *Behavioral and Brain Sciences 34*(1), 1–16.

Welch, I. (1992). Sequential sales, leaning, and cascades. *Journal of Finance 47*(2), 695–732.

Wojnicki, A. C. and D. Godes (2010, June). Signaling success: Strategically-positive word of mouth. Working Paper, University of Toronto.

Young, H. P. (2009, December). Innovation diffusion in heterogeneous populations: Contagion, social influence, and social learning. *American Economic Review 99*(5), 1899–1924.

Zajonc, R. B. (1968). Attitudinal effects of mere exposure. *Journal of Personality and Social Psychology Monograph Supplement 9*, 1–27.