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Self-Enhancing Transmission Bias and Active Investing

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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 if investors have no inherent preference over them.

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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, other forms of social interaction are 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 a recent empirical literature documents social interactions in investment decisions by individuals and money managers, including selection of individual stocks.¹

My 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. I 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. My 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)). 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).² In addition to net underperformance of asset pricing benchmarks, investing in active funds add idiosyncratic portfolio volatility associated with deviations from holding the market. 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

¹See, e.g., Kelly and O’Grada (2000), Duflo and Saez (2002, 2003), Cohen, Frazzini and Malloy (2008a, 2008b), Ivkovich and Weisbenner (2007), Brown et al. (2008), Hong, Kubik, and Stein (2004, 2005), Massa and Simonov (2005), Shive (2010), and Gray (2009).

²Carhart (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.

as the Madoff scandal also rely on investors' belief that they can identify good 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 more on reasons that are easily exchanged with others (Barber, Heath, and Odean (2003)); select small, high-beta, growth stocks; have very high portfolio turnover; and underperform the market (Barber and Odean (2000a)). The evidence mentioned earlier of contagion in stock picking by individuals and institutions is 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)).³

These considerations suggest looking beyond direct individual-level psychological biases alone, to an explanation that emerges from the process of social interaction. The explanation I 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. I call this behavior *self-enhancing transmission bias*.

Both a rational concern for reputation and psychological bias can contribute to self-enhancing transmission bias. Talking preferentially about one's successes can help maintain personal reputation. A literature from psychology and sociology on self-presentation and impression management indicates that people seek to report positively 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.

³During 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)).

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)).⁴ 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, or more cognition- or effort-intensive choice. Self-enhancing transmission bias creates an upward selection bias in the reports made to other investors about the profitability of the chosen strategy. Selection bias increases with return variance, 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 send 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 mean return).

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 value; the preference of different categories of 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 proxies for social interactiveness with stock market trading. The approach also offers new empirical implications.

A general theoretical literature on social interaction in economics focuses on the efficiency of information flows, and the effects of interactions on behavioral convergence

⁴The '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 (2010)). Motivated reasoning (Kunda (1990)), the tendency individual draws 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, Seppi, and Loewenstein (2005) find that Scandinavian investors reexamine their portfolios more frequently when the market has risen than when it has declined.

(herding).⁵ There has also been theoretical analysis of the effects of social interactions in several fields, including 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.⁶ This paper differs from this work in examining how self-enhancing transmission bias 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 individuals who adopt one of two types of investment strategies, A (Active) and P (Passive), which have different return probability distributions. A generation occurs when a single pair meet and transact. A generation consists of four stages. (1) A pair of individuals is randomly selected from the population. (2) One of these individuals randomly becomes the sender and the other the receiver.⁷ (3) The returns of the sender and receiver from their current strategies are realized. (4) The receiver either is or is not transformed into the type of the sender, where the probability of transformation is a function of sender returns.

In AA or PP pairs, there is no change. When A and P meet, the transformation

⁵Scharfstein 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.

⁶DeMarzo, 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 (2003, 2005) provides rational models of information and asset pricing when investors communicate within a social network.

⁷In actual conversations, often 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.

depends on which becomes the sender, and stochastically on the sender's return.

Generations

Let n_i be the number of type i in the current 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 $f_A + f_P = f'_A + f'_P = 1$

A pair of individuals of opposite type can randomly be selected from the population with either A or P first. The probability of first choosing an A out of the n individuals is n_A/n , and the probability of then choosing a P out of the remaining $n - 1$ individuals is $(n - n_A)/(n - 1)$. Similarly, the probability of first choosing a P out of the n individuals is $(n - n_A)/n$, and the probability of then choosing an A out of the remaining $n - 1$ individuals is $n_A/(n - 1)$. So the total probability χ that a cross-type pair is drawn is

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

where the last equation holds by the definition of f_A in (1) using the briefer notation $f \equiv f_A$.

Transformation Probabilities

Let $T_{ij}(R_i)$ be the probability that the strategy of 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. Then the probabilities that the number of A 's or P 's increases by 1 are⁸

$$\begin{aligned} Pr(n'_A = n_A + 1, n'_P = n_P - 1) &= \left(\frac{\chi}{2}\right) T_{AP}(R_A) \\ Pr(n'_P = n_P + 1, n'_A = n_A - 1) &= \left(\frac{\chi}{2}\right) T_{PA}(R_P). \end{aligned} \tag{3}$$

⁸A 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 I apply a Moran process to the spread of a cultural trait or, in the terminology of Dawkins (1976), a 'meme'.

Here $T_{AP}(R_A)$ and $T_{PA}(R_P)$, being functions of the sender's returns, are stochastic.

Population Shifts

By (3),

$$\Delta f \equiv f' - f = \begin{cases} \frac{1}{n} & \text{with probability } \frac{\chi T_{AP}(R_A)}{2} \\ -\frac{1}{n} & \text{with probability } \frac{\chi T_{PA}(R_P)}{2} \\ 0 & \text{with probability } 1 - \frac{\chi [T_{AP}(R_A) + T_{PA}(R_P)]}{2}. \end{cases} \quad (4)$$

I 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

In a mixed pair, with probability 1/2 the type A individual takes the conversational initiative ('becomes the sender'). On starting a conversation, the sender may or may not actually talk about his investments and performance. Conditional on a given individual taking the initiative, there is a probability $s(R_A)$ or $s(R_P)$ that a message is sent, resulting in a probability $T_{AP}(R_A)$ or $T_{PA}(R_P)$ (depending on which type is the sender) that a receiving individual of opposite type is transformed. I assume that the value of the sending and receiving functions 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), so the sender and receiver functions do not have i and j subscripts.

Owing to self-enhancing transmission bias, I assume that the probability that the sender of type i sends is increasing in the performance of the sender's strategy, R_i , so $s'(R_i) > 0$.⁹ The sender can, 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. I apply a linear version of the self-enhancement assumption,

$$s(R_i) = \beta R_i + \gamma, \quad \beta, \gamma > 0, \quad (5)$$

where i is the type of the sender, and where $s_i \geq 0$, so

$$R_i \geq -\frac{\gamma}{\beta}. \quad (6)$$

⁹Self-enhancing transmission bias 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 gained 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, let's e'en keep the mishap to ourselves." (March 21, 1770); quoted in Chancellor (2000) ch. 2, p. 64.

For γ sufficiently large relative to β , even if the support of the return density includes values below $-(\gamma/\beta)$, the probability that (6) is violated is arbitrarily small. Since the sending function is type-independent, β and γ have no subscripts.

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.¹⁰

The positive slope β of the sending schedule 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, self-enhancement bias should be stronger, and therefore β higher.^{11,12} 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 strongly social connected. So γ also reflects the strength of social connections. 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 from a sender with weak performance, so I assume that $r'(R_i) > 0$. This accommodates the possibility that receivers sometimes have a degree of skepticism about the selection bias in

¹⁰Reporting favorable information about ones 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)).

¹¹This 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.

¹²An 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.

the messages they receive, as well as sender lying and exaggeration.¹³

The assumption that the receiving function depends only on sender, not receiver return, is an oversimplification. It will be interesting to explore a specification in which the receiver takes into account his own return as well. This will probably not affect the main conclusions developed here, because both types have equal opportunity to become the sender. Through the sending function, this gives each type's returns an influence on its evolutionary success.

Other things equal, discounting by receivers for the upward selection bias would result in more pessimistic 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.¹⁴ 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.¹⁵ 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 (5), 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

¹³For 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 there is still a mapping summarized by the r function from the sender's return to the probability that the receiver converts.

¹⁴See, 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. For other contexts including investor decisions and their implications for capital markets, see the survey of Daniel, Hirshleifer, and Teoh (2002).

¹⁵As 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 on 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 the review of Hearst (1991)).

transaction to transaction relative to a setting with rational receiver inferences.

Since security returns are statistically hard to predict, past performance of a trading strategy tends to convey little information about its future prospects. There is evidence that investors overweight past performance and mistakenly regard it as a substantially positive indicator of future performance. Consistent with such 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, and Choi, Laibson, and Madrian (2010) find, in an experimental study, that investors often choose high fee over low fee index funds (where the funds are otherwise identical) based upon annualized returns since inception. Barber and Odean (2002) find that early adopters switched to online trading after unusually good performance; as mentioned earlier, they subsequently traded more actively, more speculatively, and less profitably. There are strong inflows by investors into top-performing mutual funds (Sirri and Tufano (1998)), even though the evidence as to whether fund performance persists is sufficiently limited that the issue is debated in the literature.

I 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 rationality is constrained, this is a useful heuristic, since 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 .¹⁶ 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,

$$r(R_i) = a(R_i)^2 + bR_i + c, \quad a, b, c \geq 0, \quad (7)$$

¹⁶To see this in more detail, suppress i subscripts, let \bar{R} denote $E[R]$, and define the function $\psi(R)$ as

$$\psi(R) \equiv r(R) - r(\bar{R}) - r'(\bar{R})(R - \bar{R}),$$

the deviation of $r(R)$ from the tangent line to r at the mean value of R , where $\psi'(\bar{R}) = 0$. The positive second derivative causes $\psi(R)$ to curve upward in a U-shape to the left and right of \bar{R} . For the r function (for which $r'(\bar{R}) > 0$), incrementally the positive second derivative increases the curve on both sides of \bar{R} relative to a straight line with constant slope $r'(\bar{R})$.

imposing parameter constraints that ensure that $r \geq 0$ almost always.¹⁷

The values of R_i on which the receiving function is increasing satisfy

$$\begin{aligned} r'(R_i) &= 2aR_i + b > 0, \quad \text{or} \\ R_i &> -\frac{b}{2a}. \end{aligned} \tag{8}$$

For b sufficiently large relative to a , the probability that (8) is violated is arbitrarily small, so the r function can be viewed as monotonic.

The parameter c measures the susceptibility of receivers—their tendency to follow the behavior of the sender. The parameter b reflects the tendency of the receiver to be persuaded by higher returns. The quadratic parameter a reflects the tendency, after allowing for the effect of a , for extreme returns to be more persuasive.

2.4 Transmission Probabilities

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

$$\begin{aligned} T_{AP}(R_A) &= r(R_A)s(R_A) \\ &= (aR_A^2 + bR_A + c)(\beta R_A + \gamma) \\ &= a\beta R_A^3 + BR_A^2 + CR_A + c\gamma, \end{aligned} \tag{9}$$

where

$$\begin{aligned} B &= a\gamma + b\beta \\ C &= b\gamma + c\beta. \end{aligned} \tag{10}$$

By symmetry,

$$T_{PA}(R_P) = a\beta R_P^3 + BR_P^2 + CR_P + c\gamma. \tag{11}$$

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 transmission derives from the effect of A versus P on the distribution of sender returns R , such as mean, variance, and skewness.

¹⁷For example, when $a = 0$, this is ensured by the condition that

$$R_i \geq -\frac{c}{b}$$

almost always. For c sufficiently large relative to b , the probability that this is violated can be made arbitrarily small, so the r function can be viewed as monotonic.

2.5 Evolution of Types Conditional on Realized Return

I first show that, owing to self-enhancing transmission bias, high return favors active investing. Given returns R_P and R_A , we can calculate the expected change in types in population fraction. We first do so conditional on a pairing AA , PP , AP , or PA (recall that the first letter denotes the sender, the second the receiver). The expected changes in the frequency of type A in the population given AP or PA are

$$\begin{aligned} E[\Delta f|AP, R_A] &= \left(T_{AP}(R_A) \times \frac{1}{n} \right) + [(1 - T_{AP}(R_A)) \times 0] = \frac{T_{AP}(R_A)}{n} \\ E[\Delta f|PA, R_P] &= \left[T_{PA}(R_P) \times \left(-\frac{1}{n} \right) \right] + [(1 - T_{AP}(R_A)) \times 0] = -\frac{T_{PA}(R_P)}{n}. \end{aligned} \quad (12)$$

The change in the frequency of type A in the population given AA or PP is deterministically zero. So taking the expectation across the different possible combinations of sender and receiver types (AA , PP , AP , PA), by (4) and (12),

$$\left(\frac{2n}{\chi} \right) E[\Delta f|R_A, R_P] = T_{AP}(R_A) - T_{PA}(R_P). \quad (13)$$

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 (13) 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 (5), and that $r''(R_A) > 0$ by (7) gives

$$\left(\frac{2n}{\chi} \right) \frac{\partial E[\Delta f|R_A, R_P]}{\partial R_A} = \frac{\partial T_{AP}(R_A)}{\partial R_A} = r'(R_A)s(R_A) + r(R_A)s'(R_A) > 0 \quad (14)$$

$$\left(\frac{2n}{\chi} \right) \frac{\partial^2 E[\Delta f|R_A, R_P]}{\partial (R_A)^2} = \frac{\partial^2 T_{AP}(R_A)}{\partial (R_A)^2} = r''(R_A)s(R_A) + 2r'(R_A)s'(R_A) > 0. \quad (15)$$

Since R_A affects T_{AP} but not T_{PA} , these formulae describe how active return affects both the expected net shift in the fraction of active investors, which reflects both inflows and outflows, and the expected unidirectional rate of conversion of passive investors to active investing. 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 .*

Broadly consistent with these predictions, Kaustia and Knüpfer (2010) provide evidence of a strong relation between returns and new participation in the stock market in Finland in the range of positive returns. Specifically, they find that 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 Knüpfer explain their findings based on what we call self-enhancing transmission bias. Proposition 1 captures this insight, and further reinforcing effects. Self-enhancing transmission bias 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 (15), 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 that investors trade more when stocks have performed well (Griffin, Nardari, and Stulz (2007)).

2.6 Strategy Return Components

Let r be the common component of returns (e.g., the market portfolio) shared by A and P , where $E[r] = 0$, and let ϵ_i be the strategy-specific component, $E[\epsilon_i] = 0$, $i = A, P$. We assume that r, ϵ_A and ϵ_P are independent, and write the returns to the two strategies as

$$\begin{aligned} R_A &= \beta_A r + \epsilon_A - D \\ R_P &= \beta_P r + \epsilon_P, \end{aligned} \tag{16}$$

where β_i is the sensitivity of strategy return to the common return component, $\beta_A > \beta_P \geq 0$. (The condition $\beta_P \geq 0$ is not needed for most of the results.) We further assume that

$\sigma_A^2 > \sigma_P^2$, $\gamma_{1A} > \gamma_{1P}$, $\gamma_{1A} > 0$, $\gamma_{1P} \leq 0$, 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 ; skewness of a mean zero variable x is defined as $\gamma_{1x} \equiv E[x^3]/\sigma_x^3$.

Since $E[r] = E[\epsilon_i] = 0$, (16) implies that P has expected return of zero, and D is the return penalty (or if negative, premium) to active trading. 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. 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) from active trading (Barber and Odean (2000b)) or from choosing an actively trading money manager.¹⁸ However, our main conclusions apply when $D \leq 0$ as well.

Specifically, 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 $E[R_A - R_P]$ (captured in (16) by D) would vary stochastically (to be fixed at the start of each period).

For example, if A ’s are attracted to high-skewness strategies (as reflected in high skewness of ϵ_A), skewness will have to be supplied by the P ’s. Such choices by P ’s can still be regarded as passive if the P ’s are selling skewness to A ’s in response to an attractive market price. In this respect skewness differs from volatility, which A ’s could potentially create by taking side bets among themselves without inducing a risk premium.

Furthermore, in a market equilibrium setting a rise in A in the population is ultimately 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 we expect a balanced frequency of A and P .

¹⁸In addition to bearing excessive idiosyncratic risk, naive investors can systematically underperform in at least two ways: by incurring extra transaction costs (in direct stock trading or by their funds), and by making correlated irrational trades that affect price, so that the stocks they buy are overpriced and the stock they sell underpriced.

2.7 Unconditional Expected Evolution of Types

We now calculate the expected change in the population fraction of A without conditioning on returns. Taking the expectation over R_A and R_P of (13) gives

$$\left(\frac{2n}{\chi}\right) E[\Delta f] = E[T_{AP}(R_A)] - E[T_{PA}(R_P)]. \quad (17)$$

so the fraction of type A increases on average if and only if $E[T_{AP}(R_A)] > E[T_{PA}(R_P)]$.

To analyze how the population evolves unconditionally, observe that by (17), $E[\Delta f]$ is proportional to $E[T_{AP}(R_A)] - E[T_{PA}(R_P)]$, so using (16), direct calculation shows that

$$\begin{aligned} T_{AP}(R_A) - T_{PA}(R_P) &= a\beta (R_A^3 - R_P^3) + B (R_A^2 - R_P^2) + C(R_A - R_P) \\ &= a\beta[(\beta_A^3 - \beta_P^3)r^3 + 3r^2(\beta_A^2\epsilon_A - \beta_P^2\epsilon_P) + 3r(\beta_A\epsilon_A^2 - \beta_P\epsilon_P^2 + \epsilon_A^3 - \epsilon_P^3)] \\ &\quad + B[(\beta_A^2 - \beta_P^2)r^2 + 2r(\beta_A\epsilon_A - \beta_P\epsilon_P) + \epsilon_A^2 - \epsilon_P^2] + C[(\beta_A - \beta_P)r + \epsilon_A - \epsilon_P] \\ &\quad + D\{-(r\beta_A + \epsilon_A)[3a\beta(r\beta_A + \epsilon_A) + 2B] - C\} + D^2[3a\beta(r\beta_A + \epsilon_A) + B] \\ &\quad - aD^3\beta. \end{aligned} \quad (18)$$

Taking the expectation over r, ϵ_A and ϵ_P and multiplying by $2n/\chi$, the expected change in frequency is, up to a constant,

$$\begin{aligned} \left(\frac{2n}{\chi}\right) E[\Delta f] &= E[T_{AP}(R_A) - T_{PA}(R_P)] \\ &= a\beta[(\beta_A^3 - \beta_P^3)\gamma_{1r}\sigma_r^3 + \gamma_{1A}\sigma_A^3 - \gamma_{1P}\sigma_P^3] + B[(\beta_A^2 - \beta_P^2)\sigma_r^2 + (\sigma_A^2 - \sigma_P^2)] \\ &\quad + Da\beta(-3\sigma_A^2 - D^2 - 3\sigma_r^2\beta_A^2) + D^2B - DC, \end{aligned} \quad (19)$$

recalling that σ denotes standard deviation and γ_1 denotes skewness.

2.7.1 Comparative Statics

To gain insight into the determinants of reproductive success of A versus P strategies, we describe comparative statics effects on the growth in the active population fraction.

Proposition 2 *If $D \approx 0$, then under the parameter constraints of the model, the expected rate of increase in the fraction of A :*

1. *Decreases with the return penalty to active trading D ;*
2. *Increases with factor skewness, γ_{1r} , if $\beta_A > \beta_P$;*

3. *Increases with active idiosyncratic skewness, γ_{1A} ; and decreases with passive idiosyncratic skewness, γ_{1P} , so long as $\sigma_P > 0$;*
4. *Increases with active idiosyncratic volatility, σ_A ; and decreases with passive idiosyncratic volatility, σ_P , so long as $\sigma_P > 0$;*
5. *Increases with the factor loading of the active strategy, β_A , and decreases with the factor loading of the passive strategy, β_P ;*
6. *Increases with the variance of the common factor, σ_r^2*
7. *Increases with self-enhancing transmission bias, β ;*
8. *Increases with the susceptibility of receivers, c ;*
9. *Increases with the sensitivity of receptiveness to returns, b ;*
10. *Increases with attention to extremes in the receiving function, a ;*
11. *Increases with the sender conversability, γ , of trading strategies.*

I discuss at footnote 19 below the condition $D \approx 0$ (which is not needed for Part 2, the second half of Part 4, and the second half of Part 5).

To show Part 1, we differentiate (19) with respect to D , the return penalty to active trading, to obtain

$$\begin{aligned} \left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f]}{\partial D} &= -3a\beta(\beta_A^2\sigma_r^2 + \sigma_A^2) + D(-3aD\beta + 2B) - C \\ &< 0 \end{aligned} \tag{20}$$

if $D < 0$ or $D \approx 0$. So the success of A decreases with D , i.e., a greater average return penalty to active trading makes A less contagious. This rather obvious prediction requires the restriction that D be sufficiently small to ensure that with high probability returns fall in the meaningful region in which the receiving function has positive slope.¹⁹

¹⁹The ambiguity for large D results from a spurious effect: for sufficiently large negative R , the slope of the quadratic receiving function turns negative. This can spuriously make a larger return penalty D to active trading more successful in transforming P 's to A 's by making big losses even bigger. This problem could be avoided by adding a cubic term in the receiving function with coefficients restricted to ensure that the slope is never negative. However, this would increase complexity without providing additional insights.

For Part 2, differentiating with respect to factor skewness γ_{1r} gives

$$\begin{aligned} \left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f]}{\partial \gamma_{1r}} &= a\beta\sigma_r^3(\beta_A^3 - \beta_P^3) \\ &> 0 \end{aligned} \tag{21}$$

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 3, differentiating with respect to active idiosyncratic skewness γ_{1A} gives

$$\begin{aligned} \left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f]}{\partial \gamma_{1A}} &= a\beta\sigma_A^3 \\ &> 0. \end{aligned} \tag{22}$$

Thus, the advantage of A over P is increasing with the idiosyncratic skewness of A . The intuition is similar to that of Part 2.

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

$$\left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f]}{\partial \gamma_{1P}} = -a\beta\sigma_P^3, \tag{23}$$

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

Part 3 implies that conversation especially encourages demand for securities with high skewness. Goetzmann and Kumar (2008) document that investors who are underdiversified tend to prefer stocks that are more volatile and are positively skewed.

Examples of skewed securities include options or ‘lottery stocks’, such as loss firms (Teoh and Zhang (2009)) or real option firms that have a small chance of a jackpot outcome. Consistent with investors favoring positively skewed stocks, there is evidence that ex ante return skewness is a negative predictor of future stock returns (Conrad, Dittmar, and Ghysels (2009)). There is also evidence from initial public offerings (Green and Hwang (2009)) 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)).

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, which contribute to portfolio skewness. Our approach

differs in that there is no inherent preference for portfolio skewness. Instead, biases in the transmission process cause the tendency to trade lottery stocks to be more 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 be more biased toward such investments.

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).²⁰

For Part 4, differentiating with respect to active idiosyncratic volatility σ_A gives

$$\begin{aligned} \left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f]}{\partial \sigma_A} &= 3a\beta\gamma_{1A}\sigma_A^2 + 2(B - 3aD\beta)\sigma_A \\ &> 0 \end{aligned} \tag{24}$$

if $D \approx 0$ or $D < 0$. Thus, if D sufficiently small, the growth of A increases with active idiosyncratic volatility σ_A . Greater return variance increases the effect of self-enhancing transmission on the part of the sender. Although not required for it, the salience to receivers of extreme returns 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 4. A further empirical implication of Part 4 is that in periods in which individual stocks have high idiosyncratic volatility, *ceteris paribus* there will be greater holding of and volume of 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.

²⁰Kumar (2009) empirically defines lottery stocks as stocks with high skewness, high volatility, and low price (all on a percentile basis). His findings therefore do not distinguish the effects of skewness versus volatility.

Differentiating with respect to passive idiosyncratic volatility σ_P gives

$$\left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f]}{\partial \sigma_P} = -3a\beta\gamma_{1P}\sigma_P^2 - 2B\sigma_P < 0 \quad (25)$$

if $\sigma_P > 0$, since $\gamma_{1P} \leq 0$. 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.²¹

Several studies have provided evidence that individual investors choose stocks with greater (especially idiosyncratic) skewness (Mitton and Vorkink (2007)), and suggesting overpricing of stocks with high idiosyncratic risk (Ang et al. (2006, 2009), Boyer, Mitton, and Vorkink (2010), Conrad, Dittmar, and Ghysels (2009) and Baker, Bradley, and Wurgler (2010); see however Bali, Cakici, and Whitelaw (2009) and Huang et al. (2010)). 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.

An individual-level explanation for these findings is prospect theory with probability weighting creates a preference for volatile portfolios and stocks (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); see also footnote 20).

For Part 5, differentiating with respect to the factor loading of the active strategy, β_A , gives

$$\left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f]}{\partial \beta_A} = 3a\beta\beta_A^2\gamma_{1r}\sigma_r^3 + 2\beta_A\sigma_r^2B - 6a\beta\beta_A\sigma_r^2D > 0 \quad (26)$$

if $D < 0$ or $D \approx 0$. 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.

²¹As discussed earlier, in an equilibrium setting where A 's demand skewness they must either be deterred by high price or must be supplied skewness by P 's. If P 's supply skewness, then the γ_1 skewness term above reinforces the negative sign of the derivative. So in either case (skewness of P strategy close to zero, or negative), this comparative statics implies that higher idiosyncratic passive volatility encouraging the spread of P .

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

$$\begin{aligned} \left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f]}{\partial \beta_P} &= -3a\beta\beta_P^2\gamma_{1r}\sigma_r^3 - 2\beta_P\sigma_r^2 B \\ &< 0. \end{aligned} \tag{27}$$

So a greater factor loading for P opposes the evolution toward A , since the wider distribution of return outcomes encourages the spread of P . Consistent with investors excessively favoring investment in stocks with high loadings, 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.

For Part 6, differentiating with respect to the variance of the common factor, σ_R^2 gives

$$\begin{aligned} \left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f]}{\partial \sigma_R^2} &= B(\beta_A^2 - \beta_P^2) \\ &> 0. \end{aligned} \tag{28}$$

So greater volatility of the common factor favors evolution toward A , since the wider distribution of return outcomes encourages the spread of the strategy with the greater loading, A by creating greater scope for self-enhancing transmission bias to operate.

This implies that *ceteris paribus* there will be greater stock market participation in time periods and countries with more volatile stock markets. 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 *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. There are, of course, other proposed explanations.

For Part 7, differentiating with respect to β , the strength of self-enhancement bias (reflecting, for example, how tight the link is between the sender's self-esteem and performance), and recalling by (10) that B is a function of β , gives

$$\begin{aligned} \left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f]}{\partial \beta} &= a(\gamma_{1A}\sigma_A^3 - \gamma_{1P}\sigma_P^3) + a\sigma_r^3(\beta_A^3 - \beta_P^3)\gamma_{1r} + b[(\beta_A^2 - \beta_P^2)\sigma_r^2 + \sigma_A^2 - \sigma_P^2] \\ &\quad + D(-3a\beta\sigma_A^2 - 3a\beta\beta_A^2\sigma_r^2 - C) + D^2B - aD^3\beta \\ &> 0 \end{aligned} \tag{29}$$

if $D \approx 0$. So greater self-enhancement bias increases the evolution toward A , because self-enhancement bias causes greater reporting of the high returns which make A enticing for receivers.

This 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 8, differentiating with respect to the susceptibility of receivers c gives

$$\begin{aligned} \left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f]}{\partial c} &= -D\beta \\ &< 0 \end{aligned} \tag{30}$$

if $D > 0$, and is positive if $D < 0$. The reason is that greater susceptibility increases the likelihood that the receiver is transformed *given that* the sender sends. Owing to self-enhancing transmission bias (as reflected in the β term above) the probability that A sends is reduced relative to the probability that P sends when the returns of A are reduced by a positive D . An implication of this is that when there are weaker pressures toward conformity (hence, less pliable receivers), there is, perhaps surprisingly, a stronger tendency for the culture to evolve toward costly, return-reducing active strategies.

For Part 9, differentiating with respect to the sensitivity of receptiveness to returns b gives

$$\begin{aligned} \left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f]}{\partial b} &= \beta[(\beta_A^2 - \beta_P^2)\sigma_r^2 + \sigma_A^2 - \sigma_P^2] + D(D\beta - \gamma) \\ &> 0 \end{aligned} \tag{31}$$

if $D \approx 0$. Greater sensitivity of receptiveness to returns helps A spread because of self-enhancing transmission bias (reflected in β). The bias toward reporting high return helps A more than P because of the higher spread in returns of A . Greater sensitivity of receptiveness by receivers to returns magnifies this difference. 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 10, 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

$$\begin{aligned} \left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f]}{\partial a} &= \beta\sigma_r^3\gamma_{1r}(\beta_A^3 - \beta_P^3) + \beta[\gamma_{1A}\sigma_A^3 - \gamma_{1P}\sigma_P^3] + \gamma[(\beta_A^2 - \beta_P^2)\sigma_r^2 + \sigma_A^2 - \sigma_P^2] \\ &\quad - 3D\beta(\beta_A^2\sigma_r^2 + \sigma_A^2) + D^2\gamma - D^3\beta \\ &> 0 \end{aligned} \tag{32}$$

if $D \approx 0$. So greater attention by receivers to extreme outcomes, a , promotes the spread of A over P . Owing to self-enhancing transmission bias, extreme high returns are more often transmitted than extreme low returns. This helps A more than P senders to convert their partners, because the active strategy more frequently generates extreme returns.

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

$$\begin{aligned} \left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f]}{\partial \gamma} &= a[(\beta_A^2 - \beta_P^2)\sigma_r^2 + \sigma_A^2 - \sigma_P^2] - bD + aD^2 \\ &> 0 \end{aligned} \tag{33}$$

if $D \approx 0$. Greater conversability γ helps the active strategy spread 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 .

The model therefore predicts 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 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 the model predicts that this will increase evolution toward active trading. In a study of 49 countries, Eleswarapu (2004) finds high stock market turnover 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 their 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 (2009)).

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 unglamorous firms that are less attractive topics of conversation, such as business-to-business vendors or suppliers of infrastructure.²² 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 locations and time periods 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 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 . The next proposition follows immediately by (19) and the parameter constraints of the model ($\beta_A > \beta_P$, $\sigma_A^2 > \sigma_P^2$, $\gamma_{1r} \geq 0$, $\gamma_{1A} > \gamma_{1P}$, $\gamma_{1A} > 0$, and $\gamma_{1P} \leq 0$).

Proposition 3 *If the return penalty to active trading D is sufficiently close to zero, then under the parameter constraints of the model, on average the fraction of active investors increases over time.*

This comes 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 self-enhancing reporting bias

²²Loughran 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.

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 .

Since the population size is finite, the population fraction evolves stochastically. However, if the population size is large, over many generations almost surely the fraction of type A will grow.

In general, models in which there is contagious adoption of innovations lead to S-shaped adoption curves (Griliches 1957). Although I do not formally derive it, there is a similar implication here when a new form of active trading becomes available. 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 have high volatility. 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.

2.8 Local 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 tend to 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 topics to be perceived as legitimate and attractive conversation topics.

A generalization of the model to include local and non-local investors generates local 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 tends to promote local stock trading and holding.

Consider a setting in which there are two assets, a stock and the riskfree asset ('cash'), and in which some investors are located near the firm's headquarters ('locals') and some are not ('outsiders'). Locals find the stock more conversable than do outsiders. If we further

assume that locals and outsiders never talk to each other, then we can apply the model separately to locals and outsiders. Let A be investing in the stock, and P be holding cash. The higher conversability of the local stock to locals implies more rapid evolution toward A for locals than for outsiders. For some parameter values, the analysis of earlier sections implies that this will cause evolution toward A for locals and (for high enough D) toward P for non-locals.

Underlying this partial equilibrium analysis are some interesting equilibrium considerations about trading between locals and outsiders. With endogenous trading of the stock, we expect the evolution toward A on the part of locals to help drive up the price of the stock, but the evolution toward P by non-locals to drive down the price. If there are many locals its price will tend to be driven high, increasing D . The resulting lower expected returns will on average reduce reported returns on A , which will tend to help drive outsiders toward P . 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 conversability 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 provides an empirical prediction that the rise of new forms of internet communication such as social networking websites should reduce 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 if, as seems plausible, such investors are more prone to be influenced in their invest decisions by conversation, and/or such investors tend to be linked more strongly to their local investor social network rather than to society at large.

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. In deriving the sending and receiving functions it is not necessary to distinguish the types, so we suppress i subscripts.

Let $\pi(R, x)$ be the profit to the sender of discussing his return R ,

$$\pi(R, x) = R + \frac{\tilde{x}}{\beta'}, \quad (34)$$

where β' is a positive constant, and component 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

$$\begin{aligned} s(R) &= Pr(x > -\beta'R | R) \\ &= 1 - F(-\beta'R), \end{aligned} \quad (35)$$

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

$$\begin{aligned} s(R) &= \frac{\tau_2 + \beta'R}{\tau_2 - \tau_1} \\ &= \frac{\tau_2}{\tau_2 - \tau_1} + \beta R, \end{aligned} \quad (36)$$

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 (36) is identical to (5) in Subsection 2.2 with

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

3.2 The Receiving Function

The most compelling intuition for a convex increasing shape for the receiving function derives from two effects: greater receiver attention to extreme outcomes (creating convexity), and, conditional upon paying attention, greater response to 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. In the appendix, we provide a different economic argument which leads to an exact quadratic receiving function.

As discussed earlier, people tend to pay closer attention to extreme outcomes. This can be reflected by having receiver attention be a positive quadratic function of the sender's return,

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

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,

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

In other words, the receiver interprets sender return as providing information about the desirability of the sender's strategy. In reality, owing to noise, past returns contain little information, so this inference is 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. To a receiver who thinks that one return observation is highly informative, suppression of bad news is less important. For example, in the limiting case in which one return observation is conclusive about the strategy's quality, a favorable return report should be taken at face value (selection bias notwithstanding).

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)). 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.

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 (7).

4 Equilibrium Trading and Returns

So far we have considered a general notion of active versus passive 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 high valuation upon a single given speculative asset, and P represents placing a low value upon it. In a setting with equilibrium price-setting, we will derive a relation between the returns on A and P similar to a special case of the specification in (16). The relation we derive will be more special in that the returns of the two strategies will be perfectly correlated, i.e., similar to (16) with $\sigma_i^2 = 0$.

4.1 Active and Passive Returns

I assume that there is a safe asset and a speculative asset. The safe asset is riskfree and in zero net supply with non-stochastic return denoted R_F . The speculative asset has a terminal value which is perceived by A 's to have expected value \bar{V}_A , and by the P 's to be \bar{V}_P , where $\bar{V}_A > \bar{V}_P$. Both perceive the variance to be σ_S^2 .

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

$$\begin{aligned} R_A &= (1 - w_A)R_F + w_A R_S \\ R_P &= (1 - w_P)R_F + w_P R_S. \end{aligned} \tag{37}$$

Investors have the mean-variance optimization problem

$$\max_{w_i} E_i[R_i] - \left(\frac{\nu}{2}\right) var(R_i), \quad i = A, P, \tag{38}$$

where ν is the coefficient of absolute risk aversion. The presence of an i subscript on the expectation but not the variance reflects the different beliefs of A and P about the expected value of the speculative investment.

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 (37) gives the optimization problems

$$\max_{w_i} (1 - w_i)R_F + w_i\bar{R}_{Si} - \left(\frac{\nu}{2}\right)w_i^2\sigma_S^2, \quad i = A, P. \quad (39)$$

Differentiating with respect to w_i and solving gives

$$w_i = \frac{\bar{R}_{Si} - R_F}{\nu\sigma_S^2}, \quad i = A, P. \quad (40)$$

Given these optimal holdings, we will derive the relationship between active and passive returns R_P and R_A , and then compare the result with the earlier return assumption (16). To obtain the relation between the returns of the two strategies, we first substitute for the portfolio weights from (40) into (37), to obtain

$$(R_i - R_F) \left(\frac{\nu\sigma_S^2}{\bar{R}_{Si} - R_F} \right) = R_S - R_F, \quad i = A, P. \quad (41)$$

Substituting $i = A, P$ and combining the two resulting equations gives

$$\begin{aligned} R_A - R_F &= \left(\frac{\bar{R}_{SA} - R_F}{\bar{R}_{SP} - R_F} \right) (R_P - R_F) \\ &= \lambda(R_P - R_F), \end{aligned} \quad (42)$$

where

$$\lambda \equiv \frac{\bar{R}_{SA} - R_F}{\bar{R}_{SP} - R_F}. \quad (43)$$

It follows by (37) that

$$\begin{aligned} R_A &= \lambda R_P + (1 - \lambda)R_F \\ &= \lambda R_P + (1 - \lambda)E[R_P] - (1 - \lambda)(E[R_P] - R_F) \\ &= \lambda R_P + (1 - \lambda)E[R_P] - (1 - \lambda)w_P(E[R_S] - R_F) \\ &= \lambda R_P + (1 - \lambda)E[R_P] - D \end{aligned} \quad (44)$$

if

$$D \equiv (1 - \lambda)w_P(E[R_S] - R_F). \quad (45)$$

In (43), 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 earn 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 (44) 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 (43) $\lambda < 0$, so $1 - \lambda > 0$, $E[R_S] - R_F < 0$, and $w_P < 0$ by (40). Together, by (45), these imply that there is a positive return penalty to active trading becomes positive, $D > 0$.

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 .

The last line of Equation (44) is consistent with (16) of Section 2 if $\sigma_A = \sigma_P = 0$ and $\lambda \equiv \beta_A/\beta_P$, except that here $E[R_P] \neq 0$ because of the non-zero expected return on the speculative asset.

A more interesting difference from (16) is that the constant term D here contains $\lambda = \beta_A/\beta_P$, and therefore reflects any difference in volatility and skewness coming from the common return component. So the comparative statics for D and return volatility in the endogenous trading model will differ from those of the reduced form model considered earlier. The endogenous trading model also contains additional parameters, such as R_F , that can potentially offer further comparative statics predictions. The model based on (16), however, is more tractable, and also applies to settings where A and P refer to different long-term or dynamic trading styles rather than a simple difference in expectations about a single risky asset.

4.2 Market Equilibrium

I assume that individuals consume all their investment returns each period, and then each individual is endowed with $1/N$ new units of wealth to invest, where N is the total number of individuals in the population. So the total amount invested by A 's is f and by P 's is $1 - f$. I further assume that the aggregate investment in the speculative asset is 1 unit of the numeraire. Then the market clearing condition requires that the value invested in the

speculative asset be equal the value outstanding of the asset,

$$fw_A + (1 - f)w_P = 1. \quad (46)$$

The expected return as perceived by type i is $\bar{R}_{Si} = (\bar{V}_i - p)/p$, $i = A, P$, so substituting for the w_i 's from (40), and solving for the price of the speculative asset p gives

$$p = \frac{f\bar{V}_A + (1 - f)\bar{V}_P}{1 + \nu\sigma_S^2 + R_F}. \quad (47)$$

By (47) and the definition of return,

$$\begin{aligned} p\bar{R}_{SA} &= \bar{V}_A - p \\ &= \frac{(1 - f)(\bar{V}_A - \bar{V}_P) + \bar{V}_A(\nu\sigma_S^2 + R_F)}{1 + \nu\sigma_S^2 + R_F}, \end{aligned} \quad (48)$$

so

$$\begin{aligned} \bar{R}_{SA} &= \frac{(1 - f)(\bar{V}_A - \bar{V}_P) + \bar{V}_A(\nu\sigma_S^2 + R_F)}{f\bar{V}_A + (1 - f)\bar{V}_P} \\ &> R_F \end{aligned} \quad (49)$$

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

Similar steps yield

$$\bar{R}_{SP} = \frac{f(\bar{V}_P - \bar{V}_A) + \bar{V}_P(\nu\sigma_S^2 + R_F)}{f\bar{V}_A + (1 - f)\bar{V}_P}. \quad (50)$$

Since the first term in the numerator is negative and the second is positive, this can be greater or less than 0 (or R_F) depending on parameter values. Since the P 's are less optimistic than the A 's they view the speculative asset as overpriced, so they underweight it relative to the holdings of the A 's. However, since it is in positive net supply, there is aggregate risk from holding A , so they may still regard it as commanding a positive risk premium. Specifically, by (40) and (50), $w_P >, < 0$ are both possible.

In different parameter ranges the returns of the P 's and A 's are either perfectly positively or negatively correlated. If the expected return premium to the speculative asset over R_F as perceived by the P 's is positive, they will hold a positive quantity (as do the A 's); if it is negative, they take a negative position. As $\bar{V}_P \rightarrow \bar{V}_A$ from below, (50) approaches $\nu\sigma_S^2 + R_F > R_F$, implying a positive perceived expected return premium above the riskfree rate. However, for given expectations of terminal value, as f varies, the perceived expected return premium can turn negative. Thus, as evolution proceeds, the correlation between the returns on A and P can change signs.²³

²³In (50), as f increases the importance of the negative first term in the numerator grows relative to the

4.3 Trading Volume

A generalization of the trading model that offers implications about volume of trade is to allow the A 's to have heterogeneous expectations about the value of the speculative asset,

$$\bar{V} + F^k, \quad E[F^k] = 0 \quad \text{for all } k, \quad (51)$$

where k is an index for the type A investors. Owing to the diversity of perceptions among the A 's, they will trade with each other, which increases volume as A increases in frequency in the population. Owing 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 $\text{var}(F^k)$ approach zero. In that case the evolution of the fractions of A 's and P 's is arbitrarily well approximated by the 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 $\text{var}(F^k)$ (i.e., $(\bar{V}_A - \bar{V}_P)/\text{var}(F^k) \rightarrow 0$), so that as the frequencies of the different types shift, the effect on volume is dominated by trading amongst A 's rather than between A 's and P 's. Then the directional prediction that volume of trade increases with the fraction of A 's remains.

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.

positive second term. So as evolution toward A proceeds, eventually the risk premium as perceived by the P 's can turn negative, so that they sell short rather than just underweight the speculative asset. At that point, by (43) λ explodes to infinity and then becomes large and negative.

5 Transmission Bias, Active Investing and Money Management

Transmission bias has broader implications for the evolution of active trading, and money management. 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.²⁴ 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.

A puzzle for classical portfolio theory is the high idiosyncratic risk of individual investors' portfolios (Goetzmann and Kumar (2008)), and the slowness of the rise of mutual funds and other diversification vehicles. Since there are large benefits to diversification, portfolio theory implies a rapid rise of low cost vehicles for diversification, and for such vehicles to spread like a prairie fire to full adoption. In reality, however, the popularity of mutual funds rose gradually over a period of decades.

People do not renew their overall portfolios allocations frequently, which reduces the frequency of triggers for conversation about portfolio selection principles. The performance of individual stocks is much more conversable than the theory of portfolio diversification, so we expect active stock picking to be more popular than the formation of passive index portfolios. Furthermore, the benefit of diversification derives from reduced risk, so there are fewer big victories and defeats, which under self-enhancing transmission bias, implies an reduced contagiousness. Finally, if investors benchmark against the market, the variability in how much a fund can beat the market is much lower if the fund is highly correlated with it.

A partially offsetting effect is that active fund-picking also generates performance outcomes that can be discussed. Active investing by mutual funds may have stimulated investor conversation and thereby assisted their rise in popularity. However, since even active mutual funds are diversified, they still tend to generate much lower extremes of volatility and skewness than individual stocks. So we expect much stronger cultural evolution toward actively picking stocks than toward actively picking active mutual funds. Thus, the cul-

²⁴Barber and Odean (2002) document that early switchers to online trading started to trade more often and more speculatively; Choi, Laibson, and Metrick (2002) document an increase in the frequency of investor trading when online trading was made available to investors in their 401(i) plans.

tural evolutionary approach is still consistent with the relatively slow rise in mutual funds (despite the huge benefits to diversification) as compared with stock picking.

The cultural evolutionary approach is also consistent with the extremely slow rise of indexing as compared with active management, despite the superior net of fees performance of indexing. The argument is similar to that for why individuals trade actively in individual stocks: when your active fund does well you brag about it, when it does badly you remain silent. Active funds provide self-enhancing conversational hooks whenever they outperform their benchmark. Indexing eliminates conversational hooks based on recent outcomes since performance matches the market index. (Of course, the indexer outperforms many particular active funds, but in most conversational contexts the more salient benchmark is the overall market index.) Thus, one of the very characteristics that make indexing good (low risk of deviating from the benchmark) makes it less culturally contagious. Of course, the advantages of indexing have been disseminated. But such arguments have to overcome the cultural evolutionary undertow of performance-biased conversational transmission that favors active funds.

In contrast with the slow rise of mutual funds, the replacement of mutual funds with ETFs in recent years has been rapid. However, this is not an evolution toward greater diversification and less active trading, it is a shift between different methods of diversification. Furthermore, one of the advantages of ETFs is that they permit more rapid moves into and out of the fund, since ETFs can be traded like stocks. In other words, ETFs accommodate more *active* investing in the form of market timing.

The rapid rise in popularity of hedge funds, despite prohibitively high fees and the difficulty for individual investors in obtaining and understanding good measures of past risk-adjusted performance, shows the strong appeal to investors of active investing. Mutual fund investing, which tends to come close to matching associated performance benchmarks, is much less worthy of conversation than making a killing through one's clever choice of a hedge fund.

Since investors reexamine their overall portfolios infrequently, the performance information that might be a pretext for bragging about one's successful fund investments only arise occasionally (e.g., with an annual or lower frequency). For example, studies of retirement investments find that most investors reallocate their portfolios extremely infrequently (Madrian and Shea (2001)). This contrasts sharply with the often high frequency of evaluation by traders of individual stocks, an extreme case being day traders.

This helps explain why day-trading as a strategy of individual investors grew rapidly during the internet boom at the turn of the millennium. Day trading is a bad idea for

most investors, as it increases risk and squanders transaction costs (see Barber and Odean (2000b) on active individual investor trading more generally). However, those engaged in day trading are likely to discuss their strategies extensively (as evidenced by the rise of investment chat rooms). So in contrast with our expectation of gradual long-term shifts in mutual fund investment, day-trading should be subject to more intense cultural evolution toward popularity. The millennial rise in day trading followed a boom-bust fad pattern; such overshooting is beyond the scope of the current model, but might be captured in future cultural evolutionary modelling.

A puzzle for the pure individual-level bias approach to asset pricing is that individual investors on the one hand seem surprisingly active and foolhardy in their individual stock trading, yet on the other seem overly reluctant to invest in the stock market in their overall portfolios (the equity premium puzzle). The argument above suggests a possible explanation: that conversational transmission biases strongly encourage active investing at the individual stock level, but much less strongly in the trading of portfolios such as a market index. This implies relatively less participation in and trading in funds than would otherwise be the case. The historically insufficient investment in funds implies an equity premium puzzle.

6 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. 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.

There are interesting possible directions for extending the approach. Realization of gains or losses may increase the conversability and salience of a strategy, resulting in an

evolution toward dynamic trading strategies over buy-and-hold strategies. If individuals can hold multiple securities in their portfolios, they may talk about their winners and remain silent about their losers. This may encourage evolution toward investment in assets with high idiosyncratic risk, or in assets whose loadings on some factors are at opposite extremes, since doing so tends to maximize the variation in performance across stocks within the portfolio.

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 the effects of biases in the transmission process.

More broadly, the approach offered here illustrates the benefits to considering cultural evolution as an explanation for patterns of trading and pricing that are not captured by existing theory. The cultural evolutionary approach also offers a way to model other issues of interest for finance. For example, it offers a possible micro-foundation for research on the spread of investor sentiment across investors. Social interactions also seem important for bubbles. 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 framework for modeling how investment ideas cause bubbles and crashes.

Appendix: Deriving a Quadratic Specification for the Receiving Function

We now derive a quadratic specification for the receiving function $r(R)$. Consider a quasi-Bayesian receiver who has a prior belief θ about the expected profitability of adopting the sender's strategy. A transaction must catch the receiver's attention before it can change this belief.

If the receiver attends, we assume that he updates θ by the formula

$$\theta' = \rho\theta + (1 - \rho)R + p, \tag{52}$$

where ρ, p are positive constants. On the RHS, $\rho\theta + (1 - \rho)R$ captures standard Bayesian updating; p reflects three possible effects. First, the very fact that another individual has adopted the trading strategy suggests that he possessed favorable information about it. This rational endorsement effect implies that $p > 0$.

Second, the *mere exposure effect* (Zajonc (1968), Bornstein and D'Agostino (1992), Moreland and Beach (1992)) is the finding that people like an unreinforced stimulus that they have been exposed to more. Based on the mere exposure effect, a receiver who had little prior awareness of the strategy will start to like it more simply by being exposed to it.

Third, 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.²⁵ This suggests that statements made by the sender in support of the sender's strategy will tend to be accepted as truth more than they were before the transaction by virtue of the fact that they have been asserted.

These effects imply that $p > 0$, which in turn implies that even observation of a *low* return from the sender can sometimes cause a switch.²⁶ So we will derive a smoothly increasing receiving function that is positive even in the region of negative returns.

The receiver's prior belief about the expected payoff of the receiver's own strategy is $q > 0$; we assume that the initial expectation for the alternative strategy is 0 ($\theta = 0$). So the receiver switches if

$$\theta' = (1 - \rho)R + p > q, \tag{53}$$

²⁵This 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)).

²⁶Another modelling route to this conclusion would be to have the switch decision depend on the difference in return between sender and receiver, with return stochastic and imperfectly correlated.

or

$$p > q(1 - \rho)R. \quad (54)$$

If the perceived value of either the individual's current strategy, q , or of the value of the endorsement, p , is stochastic, there will be a smooth probability schedule for receiver switching as a function of R . We focus on randomness in p , the influence on the receiver of the mere exposure to the sender's adoption. This makes the numerator on the RHS, $q - p$, stochastic, so that the receiving probability $r(R)$ rises smoothly with R .

Under an appropriate probability distribution of p , $r(R)$ will be quadratic. By (54), this requires that $1 - F(p)$ be quadratic, i.e., that the density $f(p)$ be linear. The linearity assumption is somewhat arbitrary; the preceding subsection provided an alternative (but slightly less tractable) approach.

Specifically, (53) implies that

$$\begin{aligned} r(R) &= Pr[p > q - (1 - \rho)R | R] \\ &= 1 - F[q - (1 - \rho)R | R]. \end{aligned} \quad (55)$$

Since the receiving function is conditional on R , the probability distribution is over p with fixed R .

Consider the linear probability density

$$f(p) = \omega_1 - 2\omega_2 p, \quad (56)$$

where ω_1 and ω_2 are positive constants, $p \in [\underline{p}, \bar{p}]$, and $f(p|R) = f(p)$ (abusing notation slightly) independent of R . This implies that

$$\begin{aligned} F(p) &= \int_{\underline{p}}^p (\omega_1 - 2\omega_2 \nu) d\nu \\ &= \omega_1(p - \underline{p}) - \omega_2(p^2 - \underline{p}^2), \end{aligned} \quad (57)$$

where \underline{p} is the lowest possible value of p .

By (55), and (57) with $p = q - (1 - \rho)R$, it follows that

$$\begin{aligned} r(R) &= 1 - \{\omega_1[q - (1 - \rho)R - \underline{p}] - \omega_2([q - (1 - \rho)R]^2 - \underline{p}^2)\} \\ &= 1 - \omega_1(q - \underline{p}) + \omega_2(q^2 - \underline{p}^2) + \\ &\quad [\omega_1(1 - \rho) - 2\omega_2q(1 - \rho)]R + \omega_2(1 - \rho)^2 R^2, \end{aligned} \quad (58)$$

which is quadratic in R , with a negative quadratic term.²⁷

²⁷We further require that $r(R)$ be upward sloping, which by (8) requires that $R \geq -b/2a$, where a is the coefficient on R^2 and b is the coefficient on R . This restriction can be satisfied by appropriate combinations of $\omega_1, \omega_2, \rho, \theta$, and q . Similarly, further parameter restrictions can ensure that $0 \leq r(R) \leq 1$.

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