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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 the bias toward active trading. In the model here, conversational biases in the social transmission of performance information favor active over passive investment strategies. Senders' propensity to communicate their returns is increasing in returns. Receivers' propensity to attend to and be converted by senders is increasing and convex in sender return. 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 assets with these characteristics even if investors have no inherent preference over them.

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1 Introduction

A neglected issue in financial economics is how investment ideas are transmitted from person to person. In most investments models, the influence of individual choices on others (possibly through information effects) is mediated by price or by quantities traded in impersonal markets. However, there is evidence that social interactions are important for investment decisions. 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 ((2000b), ch.8), discusses other studies indicating that personal conversation matters for security investment decisions, and a recent empirical literature has begun to document social interactions in investment.[1]

My purpose here is to study how the *process by which ideas are transmitted* biases social outcomes, with an application to active versus passive investment behavior. Shiller (2000a, 2000b) emphasizes that the process of conversation can cause naive popular ideas about investing to spread, and argues that conversational biases can favor superficially appealing but mistaken ideas about personal investing. I view the transmission process here as including both in-person conversation, electronic means of conversation, and one-to-many forms of communication such as blogging and news media.

A key puzzle about individual trading is that individual investors trade actively and tend to lose money by doing so relative to a passive strategy such as holding the market (Barber and Odean (2000b), Barber et al. (2009)). Furthermore, even when delegating investment decisions to institutions, investors tend to choose actively managed mutual funds over index funds (even though in the aggregate actively managed funds underperform index funds net of costs). These choices may reflect sheer ignorance, but in some cases reflect a belief by individual investors that they can identify managers that will outperform the market. The Madoff scandal, and financial con games more generally, rely on investors' belief that they can identify good investment managers.

Active investing is even more surprising in view of omission bias (Ritov and Baron (1990)), the tendency for people to be more strongly averse to the possible adverse consequences of an action (such as giving a child a vaccine) than of passivity (such as refraining from vaccinating). All else equal, holding an index funds ('passive investing') seems more like an omission, and active investing like a commission. Omission bias suggests that investors should be especially disturbed by the prospect of underperforming the market as a

[1] See, e.g., the survey of contagion in finance of Hirshleifer and Teoh (2009).

result of following an active strategy.

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 in reality seems to be greatly influenced by social interactions. For example, 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 turnover, and underperform the market (Barber and Odean (2000a)).[2]

These considerations suggest looking beyond direct individual-level psychological biases in isolation to an explanation that emerges from the process of social interaction. The explanation I propose here is based upon what I call self-enhancing transmission bias, and a failure of listeners to discount for this bias. Specifically, I assume that investors like to recount their investment victories to others more than their defeats.

This premise is supported by consideration of both rational reputational maintenance and psychological processes. Talking preferentially about one's successes can be a way to maintain personal reputation. Furthermore, there is evidence from psychology 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)).[3] 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

[2]There is also evidence that college ties affect subsequent trading of individual stocks (Massa and Simonov (2005)). Several studies provide evidence of spatial contagion in the trading of individual stocks in the U.S. and Finland (Ivkovich and Weisbenner (2007), Brown, Ivkovich, Smith, and Weisbenner (2008), and Shive (2008)). Barber and Odean (2002) find that investors who switched early to online trading subsequently began to trade more actively and speculatively, and earned reduced trading profits. It seems likely that the greater inclination or opportunity of such investors to use the web was asociated 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. Hong, Kubik, and Stein (2004) find that after controlling for wealth, race, education and risk tolerance, stock market participation increases with measures of social connectedness such as self-reports of interaction with neighbors, and church attendance. Furthermore, there is evidence impersonal social interactions (such as that between media commentators and viewers) affects trading and prices. For example, there is evidence that media coverage of individual stocks affects individual trading (Parsons and Engelberg (2009)) stock prices (temporarily; Tetlock (2007), Engelberg, Sasseville, and Williams (2009)) and the cross-section of stock returns (Fang and Peress (2009)).

[3]The 'totalitarian ego' describes the tendency in many contexts for people to filter and interpret information to the greater glory of the self (Greenwald (1980)). For example, in 'motivated reasoning' (Kunda (1990)), the individual draws inferences based on desired conclusions (e.g., that the individual possesses desirable qualities) rather than on the merits. There is also 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.

small step from thinking in a self-enhancing way to talking in such a way.

In my 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 signals about profitability of chosen strategies reported to other investors. This selection bias is stronger for strategies with high variance, as is characteristic of A. If listeners do not fully discount for the fact that they are receiving a biased sample, they will overestimate the value of adopting A over P. Furthermore, if receivers attend more to extreme outcomes, I show that high skewness strategies will have a survival advantage, because such strategies more often send the extreme high returns which are both 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 potential explanation for a range of patterns in trading and returns. These include the participation of individuals in lotteries, the preference of different categories of investors for high variance or high skewness ('lottery') stocks, overvaluation of growth firms, distressed firms and firms that have recently undertaken Initial Public Offerings (IPOs), 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 tendency for more socially interactive investors to participate more in the stock market. 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 (herding).[4] There has also been theoretical analysis 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 boom and bust patterns in investment and stock prices.[5] This

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

[5]DeMarzo, Vayanos, and Zwiebel (2001) model how information flows in social networks affect asset markets; Cipriani and Guarino (2002, 2008) model crises and herd behavior in financial markets. Welch

paper differs in examining how transmission bias affects the evolutionary outcome. There has been some modeling by economists of how cultural evolutionary processes affect ethnic and religious traits, and altruistic preferences (Bisin and Verdier (2000, 2001)). The focus here is on understanding active investment behavior.

2 The Model

2.1 The Population, Social Interactions, and Timing of Events

We consider a population of individuals who adopt one of two types of investment strategies, A (Active) and P (Passive). We define a generation as occuring when a single pair meet and transact. A generation consists of four stages. First, a pair of individuals is randomly selected from the population to interact. Second, one of these individuals is randomly selected to be the sender and the other as the receiver.[6] Third, the returns of the sender and receiver from their current strategies are realized. Fourth, 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.

When AA or PP meet, there is no change. When A and P meet, the change depends stochastically on which is selected to be the sender, and on the sender's return.

2.2 Generations and Shifts in Type Populations

Let n_i be the number of type i in the current generation and n_i' be the number in the next generation,[7] and let

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

(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.

[6] In reality when a conversation about trading occurs, sometimes both sides talk about their views and recount their experiences. Our sharp distinction between being a sender and being a receiver in a given conversation is stylized, but since we allow for the possibility that either type might be the sender, is unlikely to be misleading.

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

where $f_A + f_P = f'_A + f'_P = 1$

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

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

where the next-to-last equation holds by the definition of f_A and f_P in (1), and the last equation uses the briefer notation $f \equiv f_A$. When the population is large, the n terms vanish.

Return Performance

We will consider two alternative assumptions for costs and correlations of payoffs between A and P. We will first consider a case where the returns of the two strategies are perfectly correlated, reflecting positive holdings by the two groups of a single risky asset; and where there is a possible loss in expected return from choosing A. Later, using the assumption in (39), we allow for imperfect correlation of the two strategies, so that A can reflect either greater weighting of a common factor or the bearing of greater idiosyncratic risk.

For now, we assume that the payoffs to the active and passive strategies satisfy

$$R_A = \lambda R_P - D, \qquad \lambda > 1. \tag{3}$$

where R_A, R_P are the realized returns to A and P. In Section 4 we derive something close to this form in a setting where A and P disagree about the value of a positive-net-supply risky security, and their holdings of the security rather than the riskfree asset generate perfect correlation in return. Their We normalize $E[R_P] = 0$, so $E[R_A] = E[R_P] - D$. This form allows for higher variability and skewness of A than P.

D is the expected reduction in return from active trading. For brevity we refer to D as the 'cost') of active trading. However, a major part of the utility loss from active trading comes from excessive risk-bearing, so $D \leq 0$ 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.[8] However, in some contexts D may be negligible or negative. Our main conclusions apply when $D \leq 0$ as well.

The probability distributions of R_P and R_A can fluctuate from period to period, and generically will do so if pries are determined endogenously. Because of shifts in equilibrium prices, the values of λ and D also can vary stochastically (to be fixed at the start of each period). To avoid notational clutter we do not add time superscripts to the various variables.

Although for now we use a reduced form with exogenous returns to A and P, some equilibrium considerations should be kept in mind. As the frequency of A rises, we expect prices to move against the strategies used by A's to the extent that they are trading with P's rather than just creating side-bets against each other. Such a price effect should reduce the expected value to A, and would be reflected by an increase in D. So although the analysis derives conditions under which A increases indefinitely, in an equilibrium setting such growth would tend to be self-limiting, resulting in a balanced frequency of A and P.

Transformation Probabilities

Let $T_{ii'}(R_i)$ be the probability that the strategy of the sender, who is of type $i = A, P$, transforms the receiver, who is of type i', into type i, where $T_{ii'}$ is a function of the sender's return. Then the probabilities that the number of A's or P's increases by 1 are

$$\begin{aligned} Pr(n'_A = n_A + 1, n'_P = n_P - 1) &= \left(\frac{\chi}{2}\right) T_{AP}(R_A) \\ Pr(n'_P = n_P + 1, n'_A = n_A - 1) &= \left(\frac{\chi}{2}\right) T_{PA}(R_P). \end{aligned} \tag{4}$$

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

It follows from (4) that

$$\Delta f \equiv f' - f = \begin{cases} \frac{1}{n} & \text{with probability } \frac{\chi T_{AP}}{2} \\ -\frac{1}{n} & \text{with probability } \frac{\chi T_{PA}}{2} \\ 0 & \text{with probability } 1 - \frac{\chi[T_{AP}(R_A)+T_{PA}(R_P)]}{2}. \end{cases} \tag{5}$$

[8] 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.

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

2.3 Self-Enhancement and the Sending Function

In a heterogenous pair of individuals, with probability 1/2 type A 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 who is of the opposite type to the sender is transformed.

We assume that, for a given sender return, the value of the sending and receiving functions are independent of the sender's and receiver's types (i.e, whether the sender is A and the receiver P, or vice versa). Therefore we do not have i and i' subscripts on the sender and receiver functions.

The opportunity for a sender to talk about performance depends on how the conversation goes. In some contexts high pressure can compel a reluctant sender with poor return to disclose. In other contexts raising the topic of return may be out of place, 'flaky'. The better the sender's performance, the more he would like to discuss it, but he would also prefer not to violate conversational norms by raising self-enhancing information in conversation out of the blue. The next subsection discusses the probability that the sender, having initiated a conversation, talks about return performance.

Both casual observation and evidence from psychology indicate that people are self-enhancing in their information processing and presentation of self to others. With respect to processing of information about self, this is often referred to as 'self-serving attribution bias.' The tendency of people to internally suppress evidence suggesting that they lack desirable qualities, they will tend to automatically suppress the presentation of such evidence to others. There are also obvious possible rational reasons to deliberately present oneself positively to others.

Owing to self-enhancing transmission bias, the probability that the sender of type i sends is assumed to be increasing in the performance of the sender's strategy, R_i, so $s'(R_i) > 0$. The sender can, of course, exaggerate or simply fabricate a story of high return. We assume that senders do not always fabricate, so that the probability of sending depends on the actual return. We apply a simple linear version of the self-enhancement assumption,[9]

$$s(R_i) = \beta R_i + \gamma, \qquad \beta, \gamma \geq 0, \tag{6}$$

where i is the type of the sender. We require that $s_i \geq 0$, so

$$R_i \geq -\frac{\gamma}{\beta}. \tag{7}$$

For γ sufficiently large relative to β, even if the support of the return density includes values below $-(\gamma/\beta)$, the probability that (7) is violated is arbitrarily small.

In circumstances where the sender's self-esteem is more tightly bound to performance, we expect self-enhancement bias to be stronger, and therefore β to be higher.[10] The constant γ is a measure of the 'conversability' of the investment choice. When the investment is an attractive topic for conversation the sender raises the topic more often. It would be plausible to further distinguish conversability of A versus P, where $\gamma_A > \gamma_P$. However, we will see that the model generates survival of A even without a conversability advantage to A.

Since the sending function is type-independent, β and γ have no subscripts. Under the understanding that the argument of the sending function is the return of the sender, we suppress the i subscript on sender return R_i except when required for clarity, and denote the sending function by $s(R)$. The positive slope of the sending schedule creates a selection bias in the set of returns observed by receivers.

2.4 The Receiving Function

For a heterogeneous pair of individuals, we now consider the likelihood of a receiver of type i' 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 of strong sender performance are more persuasive than messages of weak performance, so we assume that $r'(R_i) > 0$. This accommodates the possibility that receivers sometimes have a degree of skepticism about the selection bias in the messages they receive, as well as sender lying and exaggeration.[11]

[9]Based on the high salience of extreme values, it could make sense to include a quadratic term for the sender as well, but this is not necessary for our purposes.

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

[11]If the sender always exaggerates return upward by a fixed amount, a sophisticated investor can 'undo' the bias by discounting reported returns downward by this quantity to infer the sender's actual return.

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

If a receiver does not understand that sending increases with strategy returns as given in (3), then the receiver will tend to draw 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 transaction to transaction relative to a setting with rational receiver inferences.

Receivers see a biased sample of messages about sender returns, because senders like to talk about high returns. Receivers should discount for the sender selection bias, which causes them disproportionately to see high returns. Other things equal, such discounting for selection bias would cause receivers to draw a more pessimistic inference from any given message about the desirability of the potential sender's strategy than would have been the case otherwise. However, there is extensive evidence in general that observers do not fully discount for selection biases.[12]

Although it is not needed for all our results (only for the skewness prediction), we make a further assumption 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)). When rationality is constrained, this is a useful heuristic, since extreme news tends to be highly informative. We capture this by assuming that $r''(R_i) \geq 0$. Intuitively, this assumption overlays higher attention to extreme values of R_i on an otherwise-linear relationship between receptiveness and R_i.[13]

[12] See, e.g., Nisbett and Borgida (1975), Hamill, Wilson, and Nisbett (1980), Ross, Amabile, and Steinmetz (1977), Nisbett and Ross (1980), and Brenner, Koehler, and Tversky (1996). In the context of investor decisions and implications for capital markets, see the survey of Daniel, Hirshleifer, and Teoh (2002).

[13] To see this in more detail, supress i subscripts and rewrite the receiving function as

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

where $\overline{R}$ denotes $E[R]$, and

$$\psi(R) \equiv r(R) - r(\overline{R}) - r'(\overline{R})(R - \overline{R}).$$

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

We apply a simple polynomial version of these assumptions,

$$r(R_i) = a(R_i)^2 + bR_i + c, \qquad a, b, c \geq 0. \tag{8}$$

We impose parameter constraints that ensure that $r \geq 0$ almost always. When $a = 0$, this is ensured by the condition that

$$R_i \geq -\frac{c}{b} \tag{9}$$

almost always. For c sufficiently large relative to b, the probability that (9) is violated can be made arbitrarily small, so the r function can be viewed as monotonic.[14]

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

$$\begin{aligned} r'(R_i) &= 2aR_i + b > 0, \quad \text{or} \\ R_i &> -\frac{b}{2a}. \end{aligned} \tag{10}$$

For b sufficiently large relative to a, the probability that (10) is violated is arbitrarily small, so the r function can be viewed as monotonic.

2.5 Transmission Probabilities

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

$$\begin{aligned} T_{AP}(R_A) &= r(R_A)s(R_A) \\ &= (aR_A^2 + bR_A + c)(\beta R_A + \gamma) \\ &= a\beta R_A^3 + BR_A^2 + CR_A + c\gamma, \end{aligned} \tag{11}$$

where

$$\begin{aligned} B &= a\gamma + b\beta \\ C &= b\gamma + c\beta. \end{aligned} \tag{12}$$

[14] When $a > 0$, this is an upturned parabola, so this can be ensured either by the condition $b^2 \leq 4ac$, so that there is at most one root, and in the upward sloping region of the function,

$$\text{and} \quad R_i \geq -\frac{b}{2a,}$$

or else by the condition that there are two roots, $b^2 > 4ac$, and that returns are (almost) always greater than the larger root and therefore are in the non-negative upward sloping region of the function,

$$R_i \geq \frac{-b + \sqrt{b^2 - 4ac}}{2a}.$$

Since the coefficients are all positive, the RHS is always negative, so this constraint does not rule out the occurence of negative R_i's with substantial probability.

By symmetry,

$$T_{PA}(R_P) \;=\; a\beta R_P^3 + BR_P^2 + CR_P + c\gamma, \tag{13}$$

By (10), $r'(R_A), r'(R_P) > 0$, and by (6), $s'(R_A), s'(R_P) > 0$, 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 sender type on the distribution of sender returns R. For example, if senders of type A have a more dispersed return distribution, this changes the distribution of the return messages that they send.

2.6 Evolution of Types in the Population

2.6.1 Evolution of Types Conditional on Realized Return

We will first show that, owing to self-enhancing transmission bias, high return favors active investing. Given returns R_P and R_A, we can calculated the expected change in types in population fraction. We first do so conditional on a meeting of AA, PP, AP, and 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

$$\begin{aligned} E[\Delta f|AP, R_A] &= \left(T_{AP}(R_A) \times \frac{1}{n}\right) + (0 \times 0) = \frac{T_{AP}}{n} \\ E[\Delta f|PA, R_P] &= \left[T_{PA}(R_P) \times \left(-\frac{1}{n}\right)\right] + (0 \times 0) = -\frac{T_{PA}}{n}. \end{aligned} \tag{14}$$

The change in the frequency of type A in the population given AA or PP is deterministically zero. So in the iterated expectation across the different possible combinations of sender and receiver types (AA, PP, AP, PA), the AA and PP cases contribute 0. By (5) and (14),

$$\left(\frac{2n}{\chi}\right) E[\Delta f|R_A, R_P] \;=\; T_{AP}(R_A) - T_{PA}(R_P). \tag{15}$$

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, we can partially differentiate (15) with respect to R_A with R_P constant.

Doing so 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 (6), and that $r''(R_A) > 0$ by (8) gives

$$\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f|R_A, R_P]}{\partial R_A} = \left(\frac{2n}{\chi}\right)\frac{\partial T_{AP}(R_A)}{\partial R_A} = r'(R_A)s(R_A) + r(R_A)s'(R_A) > 0 \quad (16)$$

$$\frac{\partial^2 E[\Delta f|R_A, R_P]}{(\partial R_A)^2} = \frac{\partial^2 T_{AP}(R_A)}{(\partial R_A)^2} = r''(R_A)s(R_A) + 2r'(R_A)s'(R_A) > 0 \quad (17)$$

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. A unidirectional example would be the rate at which investors who have never participated in the stock market start to participate.

Proposition 1 *When the returns to A and P are imperfectly 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 (2009) 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, higher monthly returns on the 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. The model does not imply a literally zero effect in the negative range, but a weaker effect in this range (as predicted) could be statistically hard to detect.

Kaustia and Knupfer explain their findings based on what we call self-enhancing transmission bias: a tendency of individuals with high returns to be more willing to discuss their returns than individuals with low returns. Proposition 1 captures this insight, and further reinforcing effects. Self-enhancing transmission bias is captured by $s'(R_A) = \beta > 0$. The greater willingness of receivers to convert is increasing with return, as reflected in $r'(R_A) > 0$. By (17), these together contribute to convexity of expected transformation as a function of R_A. A further contributor is the convexity of the receiver function, $r''(R_A) = a$.

We now explore the consequences of specification (3), in which the returns from A and P are perfectly correlated. By (11), (13), and (15),

$$\left(\frac{2n}{\chi}\right) E[\Delta f|R_A, R_P] = a\beta\left(R_A^3 - R_P^3\right) + B\left(R_A^2 - R_P^2\right) + C(R_A - R_P). \quad (18)$$

Substituting for R_A in terms of R_P using (3), suppressing P subscripts, and collecting terms by powers of R gives

$$\begin{aligned}\left(\frac{2n}{\chi}\right) E[\Delta f|R] &= a\beta(\lambda^3-1)R^3 + [-3a\beta\lambda^2 D + B(\lambda^2-1)]R^2 \\ &\quad +[C(\lambda-1)+3a\beta\lambda D^2 - 2B\lambda D]R - a\beta D^3 + BD^2 - CD. \quad (19)\end{aligned}$$

To see how the expected population shift toward the active strategy varies with R, we differentiate:

$$\begin{aligned}\left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f|R]}{\partial R} &= 3a\beta(\lambda^3-1)R^2 + 2[-3a\beta\lambda^2 D + B(\lambda^2-1)]R \\ &+ [C(\lambda-1)+3a\beta\lambda D^2 - 2B\lambda D]. \quad (20)\end{aligned}$$

We now give conditions under which this is positive. If $D=0$, this becomes

$$\left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f|R]}{\partial R} = 3a\beta(\lambda^3-1)R^2 + 2B(\lambda^2-1)R + C(\lambda-1). \quad (21)$$

Since the coefficients are positive, if $R>0$ this quantity is positive.

In the special case $a=0$, this further simplifies to

$$\left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f|R]}{\partial R} = 2b\beta(\lambda^2-1)R + (b\gamma + c\beta)(\lambda-1), \quad (22)$$

which is positive if

$$R > -\frac{1}{2(\lambda+1)}\left(\frac{\gamma}{\beta}+\frac{c}{b}\right). \quad (23)$$

By (7) and (9), if λ is sufficiently close to 1 this holds.

We therefore have:

Proposition 2 *If returns satisfy (3), so that active returns are a displaced magnification of passive returns, and the cost of active trading D is sufficiently small, then under the parameter restrictions of the model:*

- *If passive return $R>0$, then the expected increase in the fraction of active investors conditional on the passive return R is increasing with R;*
- *If $a=0$ (no salience of extreme returns) and if the magnification of dispersion for active trading λ is sufficiently close to 1, then the expected increase in the fraction of active investors conditional on the passive return R is increasing with R*

Intuitively, Part 2 indicates that owing to self-enhancement bias and the higher dispersion of the active strategy, higher return, which by (3) is bigger for A than P, promotes successful sending by A even more than by P. Part 1 indicates that salience of extreme outcomes can create complications that can potentially offset this effect on the downside. Both require that D be sufficiently small, because too great a penalty on A would make it unattractive to send and receive.

We next derive the unidirectional rate of conversion of P's to A's. By (11), (12), (14), and recalling that $\chi/2$ is the probability of drawing an AP pair (so that A is the sender), the expected fraction of the population converted from P to A is $(\chi/2n)T_{AP}(R_A)$. Setting $D = 0$, we can differentiate (11) with respect to R_A to obtain

$$\frac{dT_{AP}(R_A)}{dR_A} = 3a\beta R_A^2 + 2BR_A + C. \tag{24}$$

Since the coefficients are all positive, it is evident that this quantity is positive in the range where $R_A \geq 0$.

Furthermore, in the special case $a = 0$, substituting for B and C from (12), the derivative becomes

$$\frac{dT_{AP}(R_A)}{dR_A} = 2b\beta R_A + b\gamma + c\beta \tag{25}$$

which is positive if

$$R_A > -\frac{1}{2}\left(\frac{\gamma}{\beta} + \frac{c}{b}\right). \tag{26}$$

By the earlier parameter constraints (7) and (9), this inequality must hold.

Differentiating (25) a second time with respect to R_A gives

$$\frac{\partial^2 T_{AP}(R_A)}{\partial R_A^2} = 2b\beta > 0, \tag{27}$$

so the frequency of conversion to A is a convex function of R_A. We summarize these findings as follows.

Proposition 3 *If returns satisfy (3) and $D \approx 0$, then under the parameter constraints of the model:*

1. *When the active return $R_A \geq 0$, the expected one-way rate of transformation from P to A in the population is increasing with R_A;*

2. *If $a = 0$ (no extra salience of extreme returns), the expected one-way rate of transformation from P to A in the population is increasing with R_A;*

3. *If $a = 0$ the expected one-way rate of transformation from P to A in the population is convex in return R_A.*

As with Proposition 1 for the imperfect correlation case, these implications are broadly consistent with the findings of Kaustia and Knüpfer (2009) of a strong relation between returns and new participation in the stock market in Finland in the range of positive returns.

2.6.2 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 of (15) gives

$$\left(\frac{2n}{\chi}\right) E[\Delta f] = E[T_{AP}(R_A)] - E[T_{PA}(R_P)]. \tag{28}$$

so the fraction of type A increases on average if and only if $E[T_{AP}(R_A)] > E[T_{PA}(R_P)]$. Taking the expectation over R of (19) gives

$$\begin{aligned}\left(\frac{2n}{\chi}\right) E[\Delta f] &= a\beta(\lambda^3 - 1)E[R^3] + [-3a\beta\lambda^2 D + B(\lambda^2 - 1)]E[R^2] \\ &\quad - a\beta D^3 + BD^2 - CD \\ &= a\beta(\lambda^3 - 1)\gamma_1^3\sigma^3 + [-3a\beta\lambda^2 D + B(\lambda^2 - 1)]\sigma^2 \\ &\quad - a\beta D^3 + BD^2 - CD, \end{aligned} \tag{29}$$

where σ is standard deviation and γ_1 is skewness,

$$\gamma_1 \equiv \frac{E[R^3]}{\sigma^3}.$$

Proposition 4 *If the cost of active trading D is sufficiently small and skewness is non-negative, on average the fraction of active investors increases over time.*

Proof: Setting $D = 0$,

$$\left(\frac{2n}{\chi}\right) E[\Delta f] = a\beta(\lambda^3 - 1)\gamma_1^3\sigma^3 + B(\lambda^2 - 1)\sigma^2. \tag{30}$$

Since $\lambda > 1$, and assuming that skewness $\gamma_1 \geq 0$, this quantity is positive.

The expected change in the fraction of A as given in (29) is a continuous function of of D, so if D is positive but sufficiently small, the expected change in the fraction of A is still positive. $\|$

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

We now turn to comparative statics.

Proposition 5 *If $D \approx 0$, and returns satisfy (3), then under the parameter constraints of the model the expected rate of increase in the fraction of the active type:*

1. *Decreases with the cost of active trading D;*
2. *Increases with skewness γ_1^3;*
3. *Increases with volatility σ^2;*
4. *Increases with self-enhancement bias β;*
5. *Increases with the sensitivity of receptiveness to returns b;*
6. *Increases with the extent to which active trading magnifies dispersion λ;*
7. *Increases with attention to extremes in the receiving function a.*
8. *Increases with the sender conversability of trading strategies.*

We will discuss the condition $D \approx 0$ (which is not needed for the γ_1^3 and b result) below.

To show Part 1, using (29),

$$\begin{aligned}\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial D} &= -3a\beta\lambda^2\sigma^2 - 3\alpha\beta D^2 + 2BD - C \\ &< 0 \qquad (31)\end{aligned}$$

if $D \approx 0$. So the success of A decreases with D, i.e., if there is a greater average return penalty to active trading, then A becomes less contagious. This rather obvious prediction requires the restriction that D be sufficiently small to ensure that with high probability returns fall in the region where the receiving function has positive slope.[15]

[15] The ambiguity for large D results from a spurious effect: for sufficiently large negative R, the slope of the 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 effect makes no sense.

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 reduce tractability without providing additional insights.

For Part 2, taking the partial derivative with respect to skewness gives

$$\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \gamma_1^3} = a\beta(\lambda^3 - 1)\sigma^3 > 0. \tag{32}$$

Thus, the advantage of A over P is increasing with return skewness. Intuitively, extreme high returns are especially likely to be noticed and to influence the receiver when noticed. Therefore the high skewness of active strategies makes them more contagious.

This finding suggests that conversation especially encourages trading in options or in 'lottery stocks', such as loss firms (Teoh and Zhang (2009)) or real option firms that have a small chance of hitting the jackpot. There is indeed evidence from initial public offerings (Green and Hwang (2009)) and general samples (Bali, Cakici, and Whitelaw (2009)) that lottery stocks are overpriced. There is also evidence that being distressed (a characteristic that leads to a lottery distribution of payoffs) on average earn negative subsequent abnormal returns (Campbell, Hilscher, and Szilagyi (2008)).

Barberis and Huang (2008) provides a model in which prospect theory preferences create a demand for lottery stocks. Our approach differs in that there is no direct preference for lottery stocks. Instead, biases in the transmission process cause the tendency to trade lottery stocks to be more contagious. This 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, there is evidence that 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)).[16]

For Part 3, differentiating with respect to volatility σ, we see that

$$\left(\frac{n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \sigma} = 6a\beta(\lambda^3 - 1)\gamma_1^3\sigma^2 + [-6a\beta\lambda^2 D + B(\lambda^2 - 1)]\sigma > 0 \tag{33}$$

[16]Kumar (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 effects on skewness versus volatility.

if $D \approx 0$, since $\lambda > 1$ (the active strategy increases dispersion).

Thus, if D sufficiently small, the growth of A increases with return variance σ_P^2. High return variance captures receiver attention. For high return realizations, this increases the probability that the receiver switches, and for low realizations it decreases this probability. However, the high return realizations are disproportionately communicated, because of self-enhancing bias on the part of the sender.

Since most of individual stock variance is idiosyncratic (variation not explained by the market return), this finding suggests that conversation should especially encourage the purchase of stocks with high idiosyncratic risk. Several studies have provided evidence suggesting overpricing of such stocks (Ang et al. (2006, 2009) and Boyer, Mitton, and Vorkink (2009); see however Bali, Cakici, and Whitelaw (2009) and Huang et al (2009)). 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. 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 16).

For Part 4, 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 (12) that B is a function of β, gives

$$\begin{aligned} \left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \beta} &= a(\lambda^3-1)\gamma_1^3\sigma^3 + [-3a\lambda^2 D + b(\lambda^2-1)]\sigma^2 - aD^3 + bD^2 - cD \\ &> 0 \end{aligned} \tag{34}$$

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

For Part 5, receptiveness (b),

$$\begin{aligned} \left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial b} &= \beta(\lambda^2-1)\sigma^2 + \beta D^2 - \gamma D \\ &> 0 \end{aligned} \tag{35}$$

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

For Part 6, differentiating with respect to λ, the degree to which A magnifies dispersion relative to P, we find that

$$\begin{aligned}\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \lambda} &= 3a\beta\lambda^2\gamma_1^3\sigma^3 + 2\lambda(B - 3a\beta D)\sigma^2 \\ &> 0 \qquad (36)\end{aligned}$$

if $D \approx 0$. Intuitively, greater λ raises the variance and skewness of A over P; we have already seen that greater variance and skew favor A.

For Part 7, 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 yields

$$\begin{aligned}\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial a} &= \beta(\lambda^3 - 1)\gamma_1^3\sigma^3 + [-3\beta\lambda^2 D + \gamma(\lambda^2 - 1)]\sigma^2 - \beta D^3 + \gamma D^2 \\ &> 0 \qquad (37)\end{aligned}$$

if $D \approx 0$. So greater attention by receivers to extreme outcomes promotes the spread of A over P. Intuitively, owing to self-enhancing transmission bias extreme high returns are more often transmitted than extreme low returns. This helps senders of either type convert receivers. But it especially helps A's convert P's, because the active strategy more frequently generates extreme returns.

For Part 8, using (29),

$$\begin{aligned}\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \gamma} &= a(\lambda^2 - 1)\sigma^2 + aD^2 - bD \\ &> 0 \qquad (38)\end{aligned}$$

if $D \approx 0$. Greater conversability helps the active strategy because of the greater attention paid by receivers to extreme returns ($a > 0$). Extreme returns are more often the result of the A strategy. So a greater propensity to report returns (even if not conditioned on the value of those returns) tends to have a greater influence on receivers for A senders than P senders.

The decision to participate in the stock market is an active strategy (though not one that involves any penalty in expected returns). The model therefore predicts that greater social interaction throughout society will tend to increase the rate of evolution of the population toward stock market participation. Consistent with this prediction, survey evidence from ten European countries indicates that household involvement in social activities increases stock market participation Georgarakos and Pasini (2009).

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

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 firms, innovative consumer products. In contrast the model predicts neglect and underpricing of unglamourous firms that are less attractive topics of conversation, such as suppliers of infrastructure.[17] Conversational transmission biases can therefore help explain several well known empirical puzzles about investor trading and asset pricing.

Related predictions about the effects of attention have been made before (Merton (1987)). A distinctive feature here is that the prediction is based on conversation. These effects are therefore predicted to be stronger in locations and time periods with higher social interaction. This 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 so forth.

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. Conjecturally it is plausible that a generalization of the model to include local and non-local investors would generate 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 would tend to promote their purchase among locals.

A special case of such a setting derives such an implication using the current model. Suppose that locals find the local stock more conversible than do non-locals, and that locals and non-locals never talk to each other. Then we can apply the model separately to locals and non-locals. Let A be investing in the local 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 non-locals. For some parameter values this could lead to evolution toward A for

[17]Loughran and Ritter (1995) document underperformance of equity-issuing firms, including IPOs. The underperformance of growth firms is especially strong among a set of small firms that are likely to include IPO firms (Fama and French (1993)). Ang et al. (2006, 2009) document that high volatility negative predicts returns in the cross section.

locals and toward P for non-locals.

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 local and familiar stocks.

A slight generalization of the model discussed in Section 4 at equation (73) also implies greater trading of local stocks by local investors. In a setting with endogenous trading and price, if the A's have diverse valuations of their favored asset, the evolution of the population toward A tends to stimulate trading volume. This generalization implies high individual trading in firms with the 'glamour' characteristics discussed earlier, and low individual trading in mundane firms. Similarly, it suggests high local volume of trade in local firms, and high trading by individuals in the firms that are most familiar to them.

In evolutionary biology, fecundity selection acts on individuals based upon differences in their ability to produce offspring, and viability selection acts based upon differences in ability to survive long enough to reproduce. In our setting, viability means resistance to conversion by the conversational partner, and fecundity means tendency to convert one's partner. Both viability and fecundity selection are induced by the differences across types in the return distribution R_i. For example, ceteris paribus an excess of $var(R_A)$ over $var(R_P)$ contributes to greater sending on the part of active traders (fecundity selection). On the other hand, a deficit in $E[R_A]$ relative to $E[R_P]$ contributes to less sending on the part of active traders than passive traders (fecundity selection), and greater receiving on the part of active traders than passive traders (viability selection).

2.7 Imperfect Correlation between A and P

We now consider a setting where A and P are imperfectly correlated. Let r be the common component of returns ('the market') 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 andϵ_B are independent. We then write the returns to the two strategies as

$$\begin{aligned} R_A &= \beta_A r + \epsilon_A \\ R_P &= \beta_P + \epsilon_P, \end{aligned} \tag{39}$$

where β_i is the sensitivity of the return to the common return component, $\beta_A \geq \beta_P$. We further assume that $\sigma^2_{\epsilon_A} > \sigma^2_{\epsilon_P}$, $\gamma_1(\epsilon_A) > \gamma_1(\epsilon_P)$ (recalling that γ_1 denotes skewness), $\gamma_1(\epsilon_A) > 0$ and that the skewness of r is zero.

Since $E[r] = E[\epsilon_i] = 0$, (39) implies that both strategies have expected returns of zero. I have not yet incorporated any return penalty or premium D to active trading. In an explicit model of trading decisions and equilibrium price-setting, there would be risk and mispricing premia that would affect the expected values of the returns in (39). Specifically, as discussed earlier, in a market equilibrium setting a rise in A population will tend to be self-limiting because of price movement against the strategies employed by A's. Inclusion of a D parameter as in specification (3) could capture such effects at a given point in time. To modeling dynamics more fully an equilibrium setting would be needed to incorporate the effect of population evolution on expected returns.

Furthermore, 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. In this respect skewness differs from volatility, which A's can potentially create by taking side bets among themselves. So in equilibrium if the frequency of A rises and if ϵ_A retains a constant high skewness (for example), the skewness of ϵ_P may need to turn increasingly negative. 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. For now such equilibrium considerations are reflected only in the above reduced form assumptions about the parameters and the distributions of the return components.

To analyze the evolution of the population, observe that by (28), $E[\Delta f|R_A, R_P]$ is proportional to $E[T_{AP}(R_A)] - E[T_{PA}(R_P)]$, so using (39) we calculate

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

Taking the expectation over R_A and R_P and multiplying by $2n/\chi$, we describe the expected change in frequency by

$$
\begin{aligned}
\left(\frac{2n}{\chi}\right) E[\Delta f] = E[T_{AP}(R_A) - T_{PA}(R_P)] &= a\beta[\gamma_1(\epsilon_A)\sigma_{\epsilon_A}^3 - \gamma_1(\epsilon_P)\sigma_{\epsilon_P}^3] \\
&\quad + B[(\beta_A^2 - \beta_P^2\sigma_r^2 + \sigma_{\epsilon_A}^2 - \sigma_{\epsilon_P}^2)].
\end{aligned}
$$

The model with imperfectly correlated strategy returns offers comparative statics that are generally similar to those based on specification (3) with respect to the parameters shared by the two specifications. We also obtain some new comparative statics for unshared parameters.

Differentiating with respect to active idiosyncratic skewness $\gamma_1(\epsilon_A)$ gives

$$\begin{aligned}\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \gamma_1(\epsilon_A)} &= a\beta\sigma^3_{\epsilon_A} \\ &> 0. \end{aligned} \tag{40}$$

Differentiating with respect to the difference between active and passive idiosyncratic skewness $\gamma_1(\epsilon_A) - \gamma_1(\epsilon_P)$ gives

$$\begin{aligned}\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial [\gamma_1(\epsilon_A) - \gamma_1(\epsilon_P)]} &= a\beta(\sigma^3_{\epsilon_A} - \sigma^3_{\epsilon_A}) \\ &> 0. \end{aligned} \tag{41}$$

Differentiating with respect to active idiosyncratic volatility σ_{ϵ_A} gives

$$\begin{aligned}\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \sigma_{\epsilon_A}} &= 3a\beta\gamma_1(\epsilon_A)\sigma^2_{\epsilon_A} + B \\ &> 0. \end{aligned} \tag{42}$$

Differentiating with respect to passive idiosyncratic volatility σ_{ϵ_P} gives

$$\begin{aligned}\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \sigma_{\epsilon_P}} &= -3a\beta\gamma_1(\epsilon_P)\sigma^2_{\epsilon_A} - B \\ &\gtrless 0, \end{aligned} \tag{43}$$

since we have not imposed a sign on $\gamma_1(\epsilon_P)$. However, if $\gamma_1(\epsilon_P) \leq 0$ or is positive but small, then this quantity is negative.

Differentiating with respect to self-enhancement bias β gives

$$\begin{aligned}\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \beta} &= a[\gamma_1(\epsilon_A)\sigma^3_{\epsilon_A} - \gamma_1(\epsilon_P)\sigma^3_{\epsilon_P}] + b[(\beta_A^2 - \beta_P^2)\sigma_r^2 + \sigma^2_{\epsilon_A} - \sigma^2_{\epsilon_P}] \\ &> 0. \end{aligned} \tag{44}$$

Differentiating with respect to the sensitivity of receptiveness to returns b gives

$$\begin{aligned}\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial b} &= \beta[(\beta_A^2 - \beta_P^2)\sigma_r^2 + \sigma^2_{\epsilon_A} - \sigma^2_{\epsilon_P}] \\ &> 0. \end{aligned} \tag{45}$$

Differentiating with respect to attention to extremes a gives

$$\begin{aligned}\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial a} &= \beta[\gamma_1(\epsilon_A)\sigma^3_{\epsilon_A} - \gamma_1(\epsilon_P)\sigma^3_{\epsilon_P}] + \gamma[(\beta_A^2 - \beta_P^2)\sigma_r^2 + \sigma^2_{\epsilon_A} - \sigma^2_{\epsilon_P}] \\ &> 0. \end{aligned} \tag{46}$$

Differentiating with respect to sender conversability γ gives

$$\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \gamma} = a[(\beta_A^2 - \beta_P^2)\sigma_r^2 + \sigma_{\epsilon_A}^2 - \sigma_{\epsilon_P}^2] > 0. \quad (47)$$

These results are summarized as:

Proposition 6 *If returns satisfy (39), then under the parameter constraints of the model the expected rate of increase in the fraction of the active type:*

1. *Increases with the idiosyncratic skewness of A,* $\gamma_1^3(\epsilon_A)$*;*
2. *Increases with the the difference between active and passive idiosyncratic skewness* $\gamma_1(\epsilon_A) - \gamma_1(\epsilon_P)$*;*
3. *Increases with active idiosyncratic volatility* σ_{ϵ_A}*;*
4. *Decreases with passive idiosyncratic volatility* $\sigma_{\epsilon_P}^2$ *if passive idiosyncratic skewness or decreases* $\gamma_1(\epsilon_P)$ *is negative or sufficiently close to zero;*
5. *Increases with self-enhancement bias* β*;*
6. *Increases with the sensitivity of receptiveness to returns* b*;*
7. *Increases with attention to extremes in the receiving function* a*;*
8. *Increases with the sender conversability* γ *of trading strategies.*

The intuition for several of the comparative statics are identical to those given in Proposition 6. The intuition for the effect of idiosyncratic skewness and difference in idiosyncratic skewness is similar to the effect of skewness in the earlier proposition. The effect of active idiosyncratic volatility here is similar to the effect of total volatility in the earlier proposition.

The comparative statics on the effect of passive idiosyncratic volatility reflects a possible balance of effects. On the one hand, passive idiosyncratic volatility encourages the spread of P at the expense of A owing to self-enhancing transmission bias. On the other hand, passive idiosyncratic volatility amplifies the effect of passive idiosyncratic skewness $\gamma_1(\epsilon_P)$. A natural presumption might seem to be that skewness is close to zero for P, in which case this comparative statics is unambiguous. However, as 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. In either case (skewness of P strategy close to zero, or negative), this comparative statics becomes unambiguous, with higher volatility encouraging the spread of P.

3 Endogenizing the Receiving and Sending Functions

3.1 The Sending Function

We now consider how to endogenize the linear sending function. To reflect 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.

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

$$\pi_i(R, x_i) = R + \tilde{x}. \tag{48}$$

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

$$\begin{aligned} s(R) &= Pr(x > -R|R) \\ &= 1 - F(-R). \end{aligned} \tag{49}$$

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

$$s_i(R) = \frac{\tau_2 + R}{\tau_2 - \tau_1}, \tag{50}$$

where we restrict the domain of R to satisfy $\tau_1 < -R < \tau_2$ to ensure that the sending probability lies between 0 and 1. This will hold almost surely if $|\tau_1|, |\tau_2|$ are sufficiently large.

3.2 The Receiving Function

The most compelling intuition for a convex increasing shape for the receiving function is based upon two effects: greater receiver attention to extreme outcomes (creating convexity), and, conditional upon paying attention, greater response to higher return.

We will see in the next subsection that 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. This is less tractable than the quadratic specification used in Section 2. The quadratic specification can be viewed as a Taylor approximation to the cubic. In Subsection 3.2.2, we provide a different economic argument which leads exactly to a quadratic receiving function.

3.2.1 Greater Receiver Attention to Extreme Outcomes: A Cubic Specification

Let receiver attention be a positive quadratic function of the sender's return,

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

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

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

Then

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

is a cubic function with positive coefficients.

3.2.2 A Quadratic Specification

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 befor it can change this belief.

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

$$\theta' = \rho\theta + (1-\rho)R + p, \tag{51}$$

where $\rho, p > 0$ are constants. On the RHS, $\rho\theta + (1-\rho)$ 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 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 tendency of people to believe more in the truth of debatable statements that they are exposed to more often.[18] 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.[19] 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

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

or

$$p > q(1 - \rho)R. \tag{53}$$

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 (53), 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, (52) implies that

$$\begin{aligned} r(R) &= Pr[p > q - (1 - \rho)R|R] \\ &= 1 - F[q - (1 - \rho)R|R]. \end{aligned} \tag{54}$$

[18]This applies to both oral or written statements, repetitions separated by minutes or weeks apart, settings consisting primarily with new versus 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)). This is the case even if statement is mere repetition without new information content.

[19]Another 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.

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

Consider the linear probability density

$$f(p) \;=\; \omega_1 + 2\omega_2 p, \tag{55}$$

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

$$\begin{aligned} F(p) &= \int_{\underline{p}}^{p} (\omega_1 + 2\omega_2 \nu) d\nu \\ &= \omega_1 (p - \underline{p}) + \omega_2 \left(p^2 - \underline{p}^2\right), \end{aligned} \tag{56}$$

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

By (54), and (56) with $p = q - (1-\rho)R$, it follows that

$$\begin{aligned} r(R) &= 1 - \{\omega_1[q - \rho\theta - (1-\rho)R - \underline{p}] + \omega_2([q - \rho\theta - (1-\rho)R]^2 - \underline{p}^2)\} \\ &= 1 - \omega_1(q - \rho\theta - \underline{p}) + \omega_2[(q-\rho\theta)^2 - \underline{p}^2] \quad + \\ &\qquad [\omega_1(1-\rho) - 2\omega_2(q-\rho\theta)(1-\rho)]R + \omega_2(1-\rho)^2 R^2, \end{aligned} \tag{57}$$

which is quadratic in R, with a positive quadratic term.[20]

4 Equilibrium Trading and Returns

So far we have considered a general notion of active versus passive in which activity can refer to a general dynamic pattern of investing, such as day trading, margin investing, stock picking, margin 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 high valuation upon a single given speculative asset, and P represents placing a low value upon it. We will derive a relation between the returns on A and P similar to the specification in (3) in a setting with equilibrium price-setting.

[20]We further require that $r(R)$ be upward sloping, which by (10) requires that $R \geq -b/2a$, where a is the coefficient on R^2 and b is the coefficient on R, i.e.,

$$R \;\geq\; -\frac{\omega_1(1-\rho) - 2\omega_2(q-\rho\theta)(1-\rho)}{2\omega_2(1-\rho)^2}. \tag{58}$$

This restriction can be satisfied by appropriate combinations of $\omega_1, \omega_2, \rho, \theta,$ and q. Similarly, further parameter restrictions are needed to ensure that $0 \leq r(R) \leq 1$.

4.1 Active and Passive Returns

We assume that there is a safe asset and a speculative asset. The safe asset is an investment in a constant returns to scale production technology, so its return distribution is exogenously specified as R_F. The speculative asset has a terminal value which is perceived by A's to have expected value $\overline{V}_A > \overline{V}_P$, the expectation of the P's. Both perceive the variance to be σ_A^2. If the fraction of A's increases over time, the average belief of the A's dominates, so that the stock price approaches $\overline{V}_A$.

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

$$\begin{aligned} R_P &= (1 - w_P)R_F + w_P R_S \\ R_A &= (1 - w_A)R_F + w_A R_S \end{aligned} \tag{59}$$

Investors have the mean-variance optimization problem

$$\max_{w_i} E_i[R_i] - \left(\frac{\nu}{2}\right) var(R_i), \quad i = A, P \tag{60}$$

where ν is the coefficient of absolute risk aversion. The i subscript on the expectation reflects the different beliefs of A and P about the value of the speculative investment. There is no subscript to the variance because the two types agree about the variance of both investments.

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 (59) gives

$$\max_{w_i}(1 - w_i)R_F + w_i\bar{R}_{Si} - \left(\frac{\nu}{2}\right) w_i^2\sigma_S^2. \tag{61}$$

Differentiating with respect to w_i and solving gives

$$w_i = \frac{\bar{R}_{Si}}{\nu\sigma_A^2} \tag{62}$$

The A's and P's 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 $1 - f$.

Substituting for the w_i's from (62) into (59), the returns to A or P satisfy

$$(R_i - R_F)\left(\frac{\nu\sigma_A^2}{\bar{R}_{Si} - R_F}\right) = R_S - R_F, \quad i = A, P, \tag{63}$$

so

$$R_A - R_F = \left(\frac{\bar{R}_{SA} - R_F}{\bar{R}_{SP} - R_F}\right)(R_P - R_F)$$
$$= \lambda(R_P - R_F), \tag{64}$$

where

$$\lambda \equiv \left(\frac{\bar{R}_{SA} - R_F}{\bar{R}_{SP} - R_F}\right). \tag{65}$$

It follows that

$$\begin{aligned} R_A &= \lambda R_P + (1-\lambda)R_F \\ &= \lambda R_P + (1-\lambda)E[R_P] + (1-\lambda)(E[R_P] - R_F) \\ &= \lambda R_P + (1-\lambda)E[R_P] + (1-\lambda)w_P(E[R_S] - R_F). \end{aligned} \tag{66}$$

In comparing to the reduced form equation (3) in Section 2, we need to be careful about the assumption there (made only to reduce notational clutter) that $E[R_P] = 0$. Generically that assumption will fail with endogenous price. The appropriate generalization of (3) is

$$\begin{aligned} R_A &= \lambda(R_P - E[R_P]) + E[R_P] - D \\ &= \lambda R_P + (1-\lambda)E[R_P] - D. \end{aligned} \tag{67}$$

The first line makes clear that λ acts as a mean preserving spread on R_P, which has been our interpretation of (3) throughout. The second line is the same as (66) with

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

If the speculative asset is not too overpriced (expected return too low), then this shows that $D < 0$, i.e., there is a negative 'cost' of active trading.[21] Intuitively, A's earn high 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 higher expected return from investment in S. This increases the expected returns to A, but if A's overvalue the speculative asset and P's are rational, being an A rather than a P it *decreases* true expected utility of A's. This highlights the importance of distinguishing the 'cost' of active trading D from the loss of welfare from active trading. The welfare loss includes losses from excessive

[21] If the speculative asset is so overpriced that its expected return is below the riskfree rate, and if P's are rational, then they would take short positions in it, and λ as in (65) will be negative because A's and P's will in equilibrium take positions of opposite sign in the speculative asset (instead of a mere over- versus under-weighting of this positive-net-supply asset).

risk-taking. Greater transaction costs of active trading (not modeled here) would also be reflected in D.

A difference from (3) is that the constant term D contains λ, and, indirectly through the other variables, reflects return volatility. So the comparative statics for D, λ 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 (3), however, applies to broader settings where A and P refer to different trading approaches rather than a simple difference in expectations about a risky asset.

4.2 Market Equilibrium

Turning to market equilbrium, we assume that the the aggregate supply of the speculative asset is 1 unit, so the market clearing condition is

$$fw_A + (1-f)w_P = 1. \tag{68}$$

Substituting for the w_i's from (62) and solving for the price of the speculative asset p gives

$$p = \frac{f\overline{V}_A + (1-f)\overline{V}_P}{1 + \nu\sigma_A^2 + R_F}. \tag{69}$$

We can use equilibrium price to calculate the expected return on the speculative asset as perceived by A's and P's. Let the expected return as perceived by type i be denoted

$$\bar{R}_{Si} = \frac{\overline{V}_i - p}{p}, \quad i = A, P.$$

Then by (69),

$$\begin{aligned} p\bar{R}_{SA} &= \overline{V}_A - p \\ &= \frac{(1-f)(\overline{V}_A - \overline{V}_P) + \overline{V}_A(\nu\sigma^2 + R_F)}{1 + \nu\sigma^2 + R_F}, \end{aligned} \tag{70}$$

so

$$\begin{aligned} \bar{R}_{SA} &= \frac{(1-f)(\overline{V}_A - \overline{V}_P) + \overline{V}_A(\nu\sigma^2 + R_F)}{f\overline{V}_A + (1-f)\overline{V}_P} \\ &> R_F \end{aligned} \tag{71}$$

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

Similar steps yield

$$\bar{R}_{SP} \quad = \quad \frac{f(\overline{V}_P - \overline{V}_A) + \overline{V}_P(\nu\sigma^2 + R_F)}{f\overline{V}_A + (1-f)\overline{V}_P}. \tag{72}$$

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. Intuitively, 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 (62) and (72), $w_P \gtrless 0$ are both possible.

Some special cases give a sense for how parameter values determine whether there is a positive expected return premium to the speculative asset over R_F as perceived by the P's, and therefore whether they hold it positively or negatively. That in turn determines whether $\lambda \gtrless 0$. As $\overline{V}_P \to \overline{V}_A$ from above, (72) approaches $\nu\sigma^2 + R_F > R_F$. The perceived expected return reflects a risk premium above the riskfree rate, and in this case there is little perceived overvaluation to oppose this effect.

As another comparison, we see in (72) that the importance of the negative first term in the numerator grows relative to the positive second term as f increases. This shows that as evolution toward A proceeds, it is possible that a point is reached where the risk premium as perceived by the P's tunrs negative, so that they sell short rather than just underweight the speculative asset. At that point, by (65) λ explodes to infinity and then becomes large and negative. Thus, the assumption in much of the paper that $\lambda > 1$ can be violated as evolution proceeds.

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

$$\bar{V} + F^j, \qquad E[F^j] = 0 \;\; \text{for all } j, \tag{73}$$

where j is an index for the 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. Allowing diversity of the A's will make the analysis of evolution of the population more complex. But if all we are concerned about is directional predictions about volume, we can let the variance of the F_j's approach zero. In that case the analysis of reporting of returns and evolution of the fractions of A's and P's is well approximated by one where the A's trade identically and all achieve the same return. The prediction that volume of trade increases with the fraction of A's remains, though quantitatively the effect approaches zero.

5 Conclusion

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, conversational biases in the social transmission of behaviors favor active over passive trading strategies. Senders' propensity to communicate their returns is increasing in returns. Receivers' propensity to attend to and be converted by the sender is increasing and convex in sender return. Active strategies (high variance, skewness, and personal involvement) dominate the population unless the mean return penalty to active trading is too large.

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 a cultural evolutionary approach to modeling financial markets in order to explain patterns of trading and pricing that are not captured by existing theory.

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