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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 tendency to invest actively. 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, 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), ch. 8), discusses other indications that 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* affects social outcomes, with an application to active versus passive investment behavior. I view the transmission process here as including in-person conversation, electronic means of conversation, and one-to-many forms of communication such as blogging and news media. Shiller (2000a, 2000b) argues that conversational biases can favor superficially appealing but mistaken ideas about personal investing.

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 to institutions, investors favor 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 who will outperform the market. Financial scams such as the Madoff scandal 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 conse-

[1] See, 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), and Shive (2008).

quences of an action (such as giving a child a vaccine) than of passivity (refraining from vaccinating). As compared to holding an index fund ('passive investing'), active investing seems like a commission. Omission bias suggests that investors should be especially disturbed by the prospect of underperforming the market as a result of following such a 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 seems to be greatly exacerbated 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)). As discussed earlier, there is evidence of contagion in individual stock picking, 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)).[2]

These considerations suggest looking beyond direct individual-level psychological biases taken in isolation, to an explanation that emerges from the process of social interaction. The explanation I propose here is that investors like to recount their investment victories to others more than their defeats, and that listeners do not fully discount for this. I call this tendency *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. This is consistent with a literature from psychology and sociology on self-presentation and impression management in which 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,

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

so that "Impression management often involves an attempt to put the best parts of oneself into public view" (pp. 40-1). Similarly, Leary (1996 p. 4, 121) discusses tactics of selective information presentation such as concealing discreditable information.

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 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 reports to other investors about the profitability of the chosen strategy. This 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 potential explanation for a range of patterns in trading and returns. These include 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 effi-

[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)). 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.

ciency of information flows, and the effects of interactions on behavioral convergence (herding).[4] 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.[5] This paper differs from this work in examining how self-enhancing transmission bias affects the evolutionary outcome. There has been 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 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). I 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. Second, one of these individuals randomly becomes the sender and the other 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.

[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 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.

[6]In reality when a conversation occurs, sometimes both parties describe their views and 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.

When AA or PP meet, there is no change. When A and P meet, the change 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 are[7]

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

[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, 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),

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

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 who is of the opposite type to the sender 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 $s'(R_i) > 0$.[8] 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 simple version of the self-enhancement assumption,[9]

$$s(R_i) = \beta R_i + \gamma, \qquad \beta, \gamma > 0, \tag{5}$$

[8]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 gaind by one project or other in the Stocks, that my Spirit is Up with double Zeal, in the desire of our trying to enrich ourselves. ... Let but Fortune favor us, & the World will be sure to admire our Prudence. If we fail, lets een keep the mishap to ourselves." (March 21, 1770); quoted in Chancellor (2000) ch. 2, p. 64.

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

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

$$R_i \geq -\frac{\gamma}{\beta}. \tag{6}$$

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.

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]

Since the sending function is type-independent, β and γ have no subscripts. The positive slope of the sending schedule creates a selection bias in the set of returns observed by receivers.

In circumstances where the sender's self-esteem is more tightly bound to performance, self-enhancement bias should be stronger, and therefore β to be higher.[11] 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. 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, we will see that 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

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

[11] 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.

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.[12]

The assumption that the receiving function depends only on sender return, not receiver return, is an oversimplification. It will be interesting to explore 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. Through the sending function, this gives each type's return a positive influence its evolutionary success.

Receivers see a biased sample of messages about sender returns, because senders like to talk about high returns. Other things equal, discounting by receivers for 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.[13]

If a receiver does not understand that sending increases with strategy returns as implied by the sending function (5), 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 transaction to transaction relative to a setting with rational receiver inferences.

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

[12]For example, if the sender always exaggerates return upward by a fixed amount, the receiver may or may not be sophisticated enough to 'undo' this bias, but there is still a mapping summarized by r from the sender's return to the probability that the receiver is persuades to convert.

[13]See, e.g., Nisbett and Borgida (1975), Ross, Amabile, and Steinmetz (1977), Hamill, Wilson, and Nisbett (1980), 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).

receptiveness and R_i.[14]

We apply a simple polynomial version of these assumptions,

$$r(R_i) = a(R_i)^2 + bR_i + c, \qquad a, b, c \geq 0, \tag{7}$$

imposing parameter constraints that ensure that $r \geq 0$ almost always.[15]

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

$$\begin{aligned} r'(R_i) &= 2aR_i + b > 0, \quad \text{or} \\ R_i &> -\frac{b}{2a}. \end{aligned} \tag{9}$$

For b sufficiently large relative to a, the probability that (9) is violated is arbitrarily small, so the r function can be viewed as monotonic.

The parameter a measures the pliability or emulativeness of receivers; it measures their tendency to follow the behavior of the sender. The parameter b reflects the basic 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,

$$\begin{aligned} T_{AP}(R_A) &= r(R_A)s(R_A) \\ &= (aR_A^2 + bR_A + c)(\beta R_A + \gamma) \\ &= a\beta R_A^3 + BR_A^2 + CR_A + c\gamma, \end{aligned} \tag{10}$$

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

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

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

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

The function $\psi(R)$ gives the deviation of $r(R)$ from the tangent line to r at the mean value of R, so $\psi'(\bar{R}) = 0$. 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 $r'(\bar{R})$.

[15]When $a = 0$, this is ensured by the condition that

$$R_i \geq -\frac{c}{b} \tag{8}$$

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

where

$$\begin{aligned} B &= a\gamma + b\beta \\ C &= b\gamma + c\beta. \end{aligned} \tag{11}$$

By symmetry,

$$T_{PA}(R_P) = a\beta R_P^3 + BR_P^2 + CR_P + c\gamma. \tag{12}$$

By (9), $r'(R_A), r'(R_P) > 0$, and by (5), $s'(R_A), s'(R_P) > 0$, 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.

2.5 Strategy Returns

Let r be the common component of returns (e.g., the market porfolio) 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. We write the returns to the two strategies as

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

where β_i is the sensitivity of the return to the common return component, $\beta_A > \beta_P \geq 0$. (The condition $\beta_P \geq 0$ is not crucial 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 $E[r] = E[\epsilon_i] = 0$, (13) 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.[16] However, in some contexts D may be negligible or negative. Our main conclusions apply when $D \leq 0$ as well.

Specifically, in an explicit model of trading decisions and equilibrium price-setting, there would be risk and mispricing premia that would affect $E[R_A]$ and $E[R_P]$. In such a setting, equilibrium prices and therefore the probability distributions of R_P and R_A generically will fluctuate from period to period. The expected difference between the two strategies $E[R_A - R_P]$ (captured in (13) 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 affecting prices.

Furthermore, in a market equilibrium setting a rise in A in the population can be 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.

2.6 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 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

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

[16] 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.

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 (4) 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 $T_{AP}(R_A) > T_{PA}(R_P)$.

We now calculate the expected change in the population fraction of A without conditioning on returns. Taking the expectation over R of (15) gives

$$\left(\frac{2n}{\chi}\right) E[\Delta f] \;=\; E[T_{AP}(R_A)] - E[T_{PA}(R_P)]. \tag{16}$$

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

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 example the effect of increase R_A with R_P constant. Partially differentiating (15) 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

$$\left(\frac{2n}{\chi}\right) \frac{\partial E[\Delta f | R_A, R_P]}{\partial R_A} \;=\; \frac{\partial T_{AP}(R_A)}{\partial R_A} = r'(R_A)s(R_A) + r(R_A)s'(R_A) > 0 \tag{17}$$

$$\left(\frac{2n}{\chi}\right) \frac{\partial^2 E[\Delta f | R_A, R_P]}{\partial (R_A)^2} \;=\; \frac{\partial^2 T_{AP}(R_A)}{\partial (R_A)^2} = r''(R_A)s(R_A) + 2r'(R_A)s'(R_A) > 0. \tag{18}$$

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 (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, a higher monthly return on the portfolio of stocks held by individuals in a zip code neighborhood is associated with increased stock market participation by potential new investors living in that neighborhood during the next month. The greater strength of the effect in the positive than in the negative range is consistent with the convexity prediction. Furthermore, within the positive range the effect is stronger for higher returns. The model does not imply a literally zero effect in the negative range, but a weaker effect within this range (as predicted by Proposition 1) could be statistically hard to detect.

Kaustia and Knupfer explain their findings based on what we call self-enhancing transmission bias: a tendency of individuals with high returns to be more willing to discuss their strategy and performance than individuals with low returns. 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 (18), 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 Proposition 1) also implies that when the stock market rises, volume of trade will increase. This 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)).

2.7 Unconditional Expected Evolution of Types

To analyze how the population evolves unconditionally, observe that by (16), $E[\Delta f]$ is proportional to $E[T_{AP}(R_A)] - E[T_{PA}(R_P)]$, so using (13), direct calculation shows that

$$\begin{aligned} T_{AP}(R_A) - T_{PA}(R_P) &= a\beta\left(R_A^3 - R_P^3\right) + B\left(R_A^2 - R_P^2\right) + C(R_A - R_P) \\ &= a\beta[(\beta_A^3 - \beta_P^3)r^3 + 3r^2(\beta_A^2\epsilon_A - \beta_P^2\epsilon_P) + 3r(\beta_A\epsilon_A^2 - \beta_P\epsilon_P^2 + \epsilon_A^3 - \epsilon_P^3)] \\ &\quad + B[(\beta_A^2 - \beta_P^2)r^2 + 2r(\beta_A\epsilon_A - \beta_P\epsilon_P) + \epsilon_A^2 - \epsilon_P^2] + C[(\beta_A - \beta_P)r + \epsilon_A - \epsilon_P] \\ &\quad + D\{-(r\beta_A + \epsilon_A)[3a\beta(r\beta_A + \epsilon_A) + 2B] - C\} + D^2[3a\beta(r\beta_A + \epsilon_A) + B] \\ &\quad - aD^3\beta. \end{aligned} \tag{19}$$

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,

$$\begin{aligned}\left(\frac{2n}{\chi}\right) E[\Delta f] &= E[T_{AP}(R_A) - T_{PA}(R_P)] \\ &= a\beta[(\beta_A^3 - \beta_P^3)\gamma_{1r}\sigma_r^3 + \gamma_{1A}\sigma_A^3 - \gamma_{1P}\sigma_P^3] + B[(\beta_A^2 - \beta_P^2)\sigma_r^2 + (\sigma_A^2 - \sigma_P^2)] \\ &\quad + Da\beta(-3\sigma_A^2 - D^2 - 3\sigma_r^2\beta_A^2) + D^2B - DC, \end{aligned} \tag{20}$$

recalling that σ denotes standard deviation and γ_1 denotes skewness.

2.7.1 Comparative Statics

We start with comparative statics.

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};*
4. *Decreases with passive idiosyncratic skewness γ_{1P} so long as $\sigma_P > 0$;*
5. *Increases with active idiosyncratic volatility σ_A;*
6. *Decreases with passive idiosyncratic volatility σ_P so long as $\sigma_P > 0$;*
7. *Increases with the factor loading of the active strategy, β_A;*
8. *Decreases with the factor loading of the passive strategy, β_P;*
9. *Increases with the variance of the common factor, σ_R^2*
10. *Increases with self-enhancement bias β;*
11. *Increases with the pliability or emulativeness of receivers c;*
12. *Increases with the sensitivity of receptiveness to returns b;*
13. *Increases with attention to extremes in the receiving function a;*
14. *Increases with the sender conversability γ of trading strategies.*

I discuss at footnote 17 below the condition $D \approx 0$ (which is not needed for Results 2-4, 6, and 8). To show Part 1, differentiating (20) with respect to the return penalty to active trading D gives

$$\begin{aligned}\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial D} &= -3a\beta(\beta_A^2\sigma_r^2+\sigma_A^2)+D(-3aD\beta+2B)-C \\ &< 0 \end{aligned} \tag{21}$$

if $D<0$ or $D\approx 0$. 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.[17]

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

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

since $\beta_A > \beta_P$. Thus, the advantage of A over P is increasing with factor skewness. Intuitively, extreme high returns are especially likely to be sent, noticed, and to convert the receiver when noticed. If A has greater loading than P on the factor, then 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

$$\begin{aligned}\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \gamma_{1A}} &= a\beta\sigma_A^3 \\ &> 0. \end{aligned} \tag{23}$$

Thus, the advantage of A over P is increasing with the idiosyncratic skewness of A. The intuition is similar to that of Part 2, except that here it does not rely on any difference in loadings on the common factor.

For Part 4, differentiating with respect to passive idiosyncratic skewness γ_{1P} gives

$$\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \gamma_{1P}} = -a\beta\sigma_P^3, \tag{24}$$

[17]The 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.

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

The idiosyncratic skewness implication also suggests that conversation especially encourages demand for securities with high skewness. Examples include options or '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 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. There is also evidence that being distressed (a characteristic that leads to a lottery distribution of payoffs) on average leads to 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)).[18]

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

$$\begin{aligned} \left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \sigma_A} &= 3a\beta\gamma_{1A}\sigma_A^2 + 2(B - 3aD\beta)\sigma_A. \\ &> 0 \end{aligned} \tag{25}$$

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. The salience to receivers of extreme returns rein-

[18]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 the effects of skewness versus volatility.

forces this effect, since it is the extreme high returns that are disproportionately communicated.

An empirical implication of Part 5 is that in periods in which individual stocks have high idiosyncratic volatility, participation in the the stock market in the form of individual stocks will increase. Intuitively, during such periods A's have more large gains to report selectively. In such periods there we therefore expect to see greater participation and greater volume of trade.

For Part 6, differentiating with respect to passive idiosyncratic volatility σ_P gives

$$\begin{aligned}\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \sigma_P} &= -3a\beta\gamma_{1P}\sigma_P^2 - 2B\sigma_P \\ &< 0 \end{aligned} \tag{26}$$

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. Furthermore, passive idiosyncratic volatility amplifies the effect of passive idiosyncratic skewness γ_{1P}. 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. If P's supply skewness, then the 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.

Several studies have provided evidence suggesting overpricing of such stocks with high idiosyncratic risk (Ang et al. (2006, 2009), Boyer, Mitton, and Vorkink (2009), and Conrad, Dittmar, and Ghysels (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 18).

For Part 7, differentiating with respect to the factor loading of the active strategy, β_A gives

$$\begin{aligned}\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \beta_A} &= 3a\beta\beta_A^2\gamma_{1r}\sigma_r^3 + 2\beta_A\sigma_r^2 B - 6a\beta\beta_A\sigma_r^2 D \\ &> 0 \end{aligned} \tag{27}$$

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.

Similarly, for Part 8, differentiating with respect to the factor loading of the active strategy, β_A gives

$$\begin{aligned}\left(\frac{2n}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \beta_P} &= -3a\beta\beta_P^2\gamma_{1r}\sigma_r^3 - 2\beta_P\sigma_r^2 B \\ &< 0. \end{aligned} \tag{28}$$

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

For Part 10, 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 (11) that B is a function of β, gives

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

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 place a heavy premium on modesty, 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 11, differentiating with respect to the pliability/emulativeness 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 pliability 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 12, 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 the level of returns helps A spread 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 sensitivity of receptiveness by receivers to returns magnifies this difference. The analysis therefore implies, for example, that when extrapolative beliefs are stronger so that high past returns are informative about the future, the culture will tend to evolve toward active trading.

For Part 13, 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 14, 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.

Greater social interaction increases the probability that a potential sender will discuss returns, 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 unglamourous firms that are less attractive topics of conversation, such as business-to-business vendors or suppliers of infrastructure.[19] 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 social interaction. 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 chat rooms, and so forth.

2.7.2 The Evolutionary Success of Active Investing

The comparative statics provide insight into the basic issue of whether evolution favors A or P. The next proposition follows immediately by (20) and the parameter constraints of

[19]Loughran and Ritter (1995) document underperformance of equity-issuing firms, including IPOs. 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.

the model ($\beta_A \geq \beta_P$, $\sigma_A^2 > \sigma_P^2$, $\gamma_{1r} \geq 0$, $\gamma_{1A} > \gamma_{1P}$, $\gamma_{1A} > 0$, 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 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 a period of 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; a classic study is 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)).

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 psychological 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)). Local and familiar issues tend to involve greater amounts of shared information, which perhaps helps legitimize them as topics conversation.

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.

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 conversible 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 (discussed informally here) about trading between locals and outsiders. With endogenous trading of the stock, we expect the evolution toward A on the part of locals to 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 cause lower reported returns associated with A, which will tend to 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 conversibility of local stocks to locals is enough to drive 'home bias' on the part of outsiders.

There is evidence of familiarity and local biases in investing, as with home bias in favor of domestic over foreign stocks (Tesar and Werner (1995)). Huberman (2001) provides evidence that investors tend to choose locally familiar stocks. The analysis here implies that such effects will be stronger in localities in which there is much higher social interaction within localities than across them.

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.

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

$$\pi_i(R, x_i) = R + \frac{\tilde{x}}{\beta'}, \tag{34}$$

where β' is a positive constant. 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

$$\begin{aligned} s(R) &= Pr\left(x > -\beta' R | R\right) \\ &= 1 - F(-\beta' R). \end{aligned} \tag{35}$$

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

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

where $\beta \equiv \beta'/(\tau_2 - \tau_1)$, and 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. 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. 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 to an exact quadratic receiving function.

3.2.1 Greater Receiver Attention to Extreme Outcomes: A Cubic Specification

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,

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

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

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

In other words, the receiver interprets sender return as providing information about the desirability of the sender's strategy. 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 before it can change this belief.

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

$$\theta' = \rho\theta + (1-\rho)R + p, \tag{37}$$

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 tendency of people to believe more in the truth of debatable statements that they are exposed to more often.[20] 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.[21] 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

$$\theta' = (1 - \rho)R + p > q, \tag{38}$$

or

$$p > q(1 - \rho)R. \tag{39}$$

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 (39), 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, (38) implies that

$$\begin{aligned} r(R) &= Pr[p > q - (1 - \rho)R|R] \\ &= 1 - F[q - (1 - \rho)R|R]. \end{aligned} \tag{40}$$

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

[20] 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.

[21] 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.

Consider the linear probability density

$$f(p) \;=\; \omega_1 - 2\omega_2 p, \tag{41}$$

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

$$\begin{aligned} F(p) &= \int_{\underline{p}}^{p} (\omega_1 - 2\omega_2 \nu) d\nu \\ &= \omega_1(p - \underline{p}) - \omega_2 \left(p^2 - \underline{p}^2\right), \end{aligned} \tag{42}$$

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

By (40), and (42) with $p = q - (1-\rho)R$, it follows that

$$\begin{aligned} r(R) &= 1 - \{\omega_1[q - -(1-\rho)R - \underline{p}] - \omega_2([q - (1-\rho)R]^2 - \underline{p}^2)\} \\ &= 1 - \omega_1(q - \underline{p}) + \omega_2[q^2 - \underline{p}^2] \;\; + \\ &\qquad [\omega_1(1-\rho) - 2\omega_2 q(1-\rho)]R + \omega_2(1-\rho)^2 R^2, \end{aligned} \tag{43}$$

which is quadratic in R, with a negative quadratic term.[22]

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 (13). The relation we derive will be more special in that the returns of the two strategies will be perfectly correlated, i.e., similar to (13) with $\sigma_i^2 = 0$.

[22] We further require that $r(R)$ be upward sloping, which by (9) 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 $0 \leq r(R) \leq 1$.

4.1 Active and Passive Returns

I assume that there is a safe asset and a speculative asset. The safe asset is an investment in a constant returns to scale investment technology with exogenously non-stochastic return R_F. The speculative asset has a terminal value which is perceived by A's to have expected value $\overline{V}_A$, and by the P's to be $\overline{V}_P$, where $\overline{V}_A > \overline{V}_P$. 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

$$\begin{aligned} R_A &= (1-w_A)R_F + w_A R_S \\ R_P &= (1-w_P)R_F + w_P R_S. \end{aligned} \tag{44}$$

Investors have the mean-variance optimization problem

$$\max_{w_i} E_i[R_i] - \left(\frac{\nu}{2}\right) var(R_i), \quad i = A, P, \tag{45}$$

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 (44) gives the optimization problems

$$\max_{w_i} \ (1-w_i)R_F + w_i\bar{R}_{Si} - \left(\frac{\nu}{2}\right) w_i^2\sigma_S^2, \quad i = A, P. \tag{46}$$

Differentiating with respect to w_i and solving gives

$$w_i = \frac{\bar{R}_{Si} - R_F}{\nu\sigma_S^2}. \tag{47}$$

Given these optimal holdings of A and P, 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 (13). We first substitute for the w_i's from (47) into (44), to obtain the returns to strategy i:

$$(R_i - R_F)\left(\frac{\nu\sigma_S^2}{\bar{R}_{Si} - R_F}\right) = R_S - R_F, \quad i = A, P. \tag{48}$$

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

$$\begin{aligned} R_A - R_F &= \left(\frac{\bar{R}_{SA} - R_F}{\bar{R}_{SP} - R_F}\right)(R_P - R_F) \\ &= \lambda(R_P - R_F), \end{aligned} \tag{49}$$

where

$$\lambda \equiv \frac{\bar{R}_{SA} - R_F}{\bar{R}_{SP} - R_F}. \tag{50}$$

It follows by (44) that

$$\begin{aligned} R_A &= \lambda R_P + (1-\lambda) R_F \\ &= \lambda R_P + (1-\lambda) E[R_P] - (1-\lambda)(E[R_P] - R_F) \\ &= \lambda R_P + (1-\lambda) E[R_P] - (1-\lambda) w_P (E[R_S] - R_F) \\ &= \lambda R_P + (1-\lambda) E[R_P] - D \end{aligned} \tag{51}$$

if

$$D \equiv (1-\lambda) w_P (E[R_S] - R_F). \tag{52}$$

By (50), since A's are more optimistic than P's about the speculative asset. either $\lambda > 1$ (if its denominator is positive) or $\lambda < 0$ (if its denominator is negative). If the speculative asset is not too overpriced, it will earns a positive risk premium over the riskfree asset and will be perceived to do so by the P's, implying $\lambda > 1$. It follows that $D < 0$, a negative return penalty to active trading. Intuitively, 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 (50) $\lambda < 0$, so $1 - \lambda > 0$, $E[R_S] - R_F < 0$, and $w_P < 0$. Together, by (52), these imply that the 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* true expected utility of A's. This highlights the importance of distinguishing the return penalty to active trading D from the loss of welfare from active trading. The welfare loss includes losses from excessive risk-taking. Greater transaction costs of active trading (not modeled here) would also be reflected in D.

The last line of Equation (51) is consistent with (13) of Section 2 if $\sigma_A = \sigma_P = 0$ and $\lambda \equiv \beta_A/\beta_P$. A minor difference in the models is that here $E[R_P] \neq 0$ because of the non-zero expected return on the speculative asset.

A more interesting difference from (13) 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 (13), however, is simpler, 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 supply of the speculative asset is 1 unit of the numeraire, and that the riskfree asset is in zero net supply. Then the market clearing condition requires that the value invested in the speculative asset be equal the value outstanding of the asset,

$$fw_A + (1-f)w_P = 1. \tag{53}$$

The expected return as perceived by type i is $\bar{R}_{Si} = (\overline{V}_i - p)/p$, $i = A, P$, so substituting for the w_i's from (47), and solving for the price of the speculative asset p gives

$$p = \frac{f\overline{V}_A + (1-f)\overline{V}_P}{1 + \nu\sigma_S^2 + R_F}. \tag{54}$$

By (54) and the definition of return,

$$\begin{aligned} p\bar{R}_{SA} &= \overline{V}_A - p \\ &= \frac{(1-f)(\overline{V}_A - \overline{V}_P) + \overline{V}_A(\nu\sigma_S^2 + R_F)}{1 + \nu\sigma_S^2 + R_F}, \end{aligned} \tag{55}$$

so

$$\begin{aligned} \bar{R}_{SA} &= \frac{(1-f)(\overline{V}_A - \overline{V}_P) + \overline{V}_A(\nu\sigma_S^2 + R_F)}{f\overline{V}_A + (1-f)\overline{V}_P} \\ &> R_F \end{aligned} \tag{56}$$

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

Similar steps yield

$$\bar{R}_{SP} = \frac{f(\overline{V}_P - \overline{V}_A) + \overline{V}_P(\nu\sigma_S^2 + R_F)}{f\overline{V}_A + (1-f)\overline{V}_P}. \tag{57}$$

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 (47) and (57), $w_P >, < 0$ 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); they take a negative position. As $\overline{V}_P \to \overline{V}_A$ from below, (57) 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]

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,

$$\overline{V} + F^k, \qquad E[F^k] = 0 \ \text{ for all } k, \tag{58}$$

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. Allowing diversity of the A's will make the analysis of evolution of the population more complex.

However, if all we are concerned about is directional predictions about volume, we can let $var(F^k)$ 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. The directional prediction that volume of trade increases with the fraction of A's remains, though the magnitude of the effect becomes small. Thus, the comparative statics predictions from Proposition 2 about the conditions under which the expected fraction of A's grows also

[23] In (57), as f increases the importance of the negative first term in the numerator grows relative to the positive second term. So as evolution toward A proceeds, eventually the risk premium as perceived by the P's can turns negative, so that they sell short rather than just underweight the speculative asset. At that point, by (50) λ explodes to infinity and then becomes large and negative.

provide predictions about what determines increased trading volume. Similar, 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, the stochastic shift in population fractions between 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 will be increasing with the proxies for the degree of social connectedness.

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.

Conversations are often influenced by chance circumstances, subtle cues, and minor costs and benefits to the transactors. This suggests that seemingly minor variations in social environment or circumstances 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 and more shifts in price and trading.

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, and a framework for modeling bubbles and crashes.

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