Social Transmission Bias and Active Investing*

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Abstract

Individual investors often invest actively and lose thereby. Social interaction seems to exacerbate this tendency. In our model, senders' propensity to discuss their strategies' returns, and receivers' propensity to be converted, are increasing in sender return. A distinctive implication is that the rate of conversion of investors to active investing is convex in sender return. Unconditionally, active strategies (high variance, skewness, and personal involvement) dominate the population unless the return penalty to active investing is too large. Thus, the model can explain overvaluation of 'active' asset characteristics even when investors have no inherent preference over them. In contrast with nonsocial approaches, sociability and other features of the sending and receiving processes are determinants of the popularity of active investing and the pricing of active strategies.

JEL Classification: G11, G12

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1 Introduction

A neglected topic in financial economics is how investment ideas are transmitted from person to person. In most investments models, the influence of individual choices on others is mediated by price or by quantities traded in impersonal markets. However, more direct forms of social interaction also matter 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 referred to direct personal contact; personal interaction was also important for institutional investors (Shiller and Pound 1989). Furthermore, an empirical literature finds that social interactions affect investment decisions by individuals and money managers, including selection of individual stocks.[1]

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

It is a remarkable fact that individual investors trade actively and have invested in active investment funds for decades, and thereby have on average underperformed net of costs relative to a passive strategy such as holding a market index—the active investing puzzle.[2] In addition to underperforming relative to factor benchmarks, trading in individual stocks and investing in active funds adds idiosyncratic portfolio volatility. For example, Calvet, Campbell, and Sodini (2007) report that idiosyncratic risk exposure of Swedish households accounts for half of the return variance for the median household.

Active investing reflects a belief of individual investors in their ability either to identify stocks or funds that will outperform the market. Financial scams such as the Madoff scheme

[1] Shiller (1990, 2000b) discusses other indications that conversation matters for security investment decisions and bubbles. The empirical literature includes Kelly and O'Grada (2000), Duflo and Saez (2002, 2003), Cohen, Frazzini and Malloy (2008, 2010), Ivković and Weisbenner (2007), Brown et al. (2008), Hong, Kubik, and Stein (2004, 2005), Massa and Simonov (2005), Shive (2010), Gray, Crawford, and Kern (2012), and Mitton, Vorkink, and Wright (2012).

[2] On underperformance in individual trading, see Barber and Odean (2000b), Barber et al. (2009). Carhart (1997) and Daniel et al. (1997) find that active funds typically do not outperform passive benchmarks. French (2008) documents very large fees paid in the aggregate by investors to active funds.

also rely on investors' belief that they can identify superior investment managers.

A plausible explanation for excessive investor trading is overconfidence (DeBondt and Thaler 1995; Barber and Odean 2000b), a basic feature of individual psychology. However, trading aggressiveness is greatly exacerbated by social interactions. For example, participants in investment clubs seem to select individual stocks based on reasons that are easily exchanged with others (Barber, Heath, and Odean 2003); select small, high-beta, growth stocks; turn over their portfolios very frequently; and underperform the market (Barber and Odean 2000a). Contagion in stock picking by individuals and institutions spreads a type of speculative behavior. Furthermore, stock market participation increases with measures of social connectedness (Hong, Kubik, and Stein 2004; Kaustia and Knüpfer 2012).[3]

These facts suggest looking beyond direct individual-level psychological biases alone, to an explanation based on *social interaction*. However, the sheer fact of contagion in investment choice, as documented in recent work, does not in itself explain a tilt toward active investing strategies. Either active or passive strategies can spread from person to person. This paper explicitly models *biases* in the transmission process—biases which endogenously turn out to promote active over passive investing. Our model offers a rich set of further testable implications, such as convexity in the relation between conversion to a new strategy and its past returns, and a greater attraction of more sociable investors to high variance and high skew strategies.

A key piece of the explanation that we propose here is that investors like to recount to others their investment victories more than their defeats, and that listeners do not fully discount for this. We call this behavior *self-enhancing transmission bias*, or *SET*. Consistent with self-enhancing thought processes and financial behavior, Karlsson, Loewenstein, and Seppi (2009) and Sicherman et al. (2012) find that Scandinavian and U.S. investors reexamine their portfolios more frequently when the market has risen than when it has declined. Consistent with *SET*, for a wide set of consumer products, positive word-of-mouth discussion of user experiences tends to predominate over negative discussion (see the review of East, Hammond, and Wright (2007)), perhaps because users want to persuade others that they are expert at product choice (Wojnicki and Godes 2008). Consistent with *SET* in investing behavior, in a database drawn from a Facebook style social network for individual investors, Heimer and Simon (2014) report that traders are more likely to initiate

[3]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; Choi, Laibson, and Metrick 2002). Early internet investors probably had greater access to and interest in online forms of social interaction, such as e-mail and investment chat rooms. Internet discussions rooms were, according to media reports, important in stimulating day trading.

communication with others when they experience strong short-term gains.[4]

Both a rational concern for reputation and psychological bias can contribute to *SET*. Research on self-presentation and impression management finds that people seek to report positively about themselves, as constrained by the need to be plausible and to satisfy presentational norms (Goffman 1961; Schlenker 1980). In a review of the impression management field, Leary and Kowalski (1990) discuss how people tend to avoid lying, but selectively omit information, so that "Impression management often involves an attempt to put the best parts of oneself into public view" (pp. 40-1).

There is also evidence of internal self-enhancing thought processes, such as the tendency of people to attribute successes to their own virtues, and failures to external circumstances or luck (Bem 1972; Langer and Roth 1975). Self-enhancing psychological processes encourage people to think more about their successes than their failures (as in the model Benabou and Tirole (2002)). It is a small step from thinking in a self-enhancing way to talking that way.

In our model, investors adopt either an Active (A) or Passive (P) investment strategy. We interpret A as the riskier option, or alternatively, the more engaging one (meaning that adopters are, all else equal, more likely to talk about it, perhaps because it is more novel, affect-laden, or arousing). *SET* creates an upward selection bias in the reports received by other investors about the profitability of the chosen strategy: they hear about good outcomes more than bad outcomes. The size of the selection bias increases with return variance; for example, if variance is zero the selection bias vanishes. We further assume that listeners do not fully discount for the biased sample of return reports they receive, and that they regard past performance as indicative of future performance. So if A has higher variance than P, receivers overestimate the value of adopting A relative to P, so A spreads through the investor population.

SET is a feature of what we call the *sending schedule*, which gives the probability that the sender reports the sender's return outcome as a function of that return. The *receiving schedule* is defined as the probability that a given reported return will convert the receiver to the strategy of the sender. The more general contribution of the model is to describe the interplay between the probability distribution of strategy return outcomes with the shapes of both the sending schedule and receiving schedule in determining the spread of competing investing strategies.[5]

[4] A one standard deviation higher weekly returns is associated with a 7% higher probability of contacting other traders in a given week.

[5] Although *SET*, a characteristic of the sending schedule, is a key contributor to the spread of active

As an illustration of the importance of the receiving schedule, suppose that receivers attend more to extreme outcomes, which tends to increase the probability of their being converted (relative to a linear increasing receiving schedule), i.e., it makes the receiving function convex. This makes extreme returns incrementally more persuasive to the receiver (though it is always still the case that higher returns are more persuasive than lower returns). High salience of extreme outcomes also promotes strategies with high volatility, because such strategies generate extreme returns more often.

The shapes of the sending and receiving function also interact to generate simple and important consequences. When there is both *SET* on the part of senders and salience of extreme returns on the part of receivers, we show that high skewness strategies tend to spread—even after controlling for volatility. The reason that this occurs is that positive skew strategies more often generate the extreme high returns which are most often reported, attended to, and influential. As a result, A spreads through the population unless it has a sufficiently strong offsetting disadvantage (lower expected return).

Finally, if A is more engaging than P as a conversation topic (more *conversable*, in our terminology), then A is recommended and its return reported to current adopters of P more often than reports about P are made to adopters of A. This favors the spread of A.

Despite the simplicity of our model assumptions, *SET*, and more generally, understanding the transmission of investing behavior in terms of the shapes of investor sending and receiving functions, helps explain a surprisingly wide range of patterns in trading and returns. These include the convexity of new participation in investment strategies as a function of past performance;[6] the participation of individuals in lotteries with negative expected return; the preference of some investors for high variance or high skewness ('lottery') stocks; overvaluation of growth firms, distressed firms, firms that have recently undertaken Initial Public Offerings (IPOs), and high volatility firms; and 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).

There are alternative theories that offer piecemeal explanations for subsets of these facts; our framework provides a unified explanation. Furthermore, our framework offers

investing, both sending and receiving schedules matter (as do the underlying psychological forces that determine them). For example, in Subsection 2.7.2 we discuss how salience of extreme outcomes to receivers also promotes strategies with high volatility.

[6]The convexity implication is consistent with evidence of disproportionate inflows to strongly-performing mutual funds. Kaustia and Knüpfer (2012) provide evidence of such convexity in new stock market participation as a function of neighbor's recent stock return. Our model predicts this effect as a result of interactions between the shapes of the sending and receiving functions.

an explanation for why several of these effects are associated with proxies for sociability, as documented in several studies[7] It similarly predicts that sociability will affect the slope and convexity of the new adoption of active investing as a function of the past returns on active strategies. Our framework also offers new empirical implications based on the effects of varying other characteristics of the sending and receiving functions, such as *SET* and the tendency of receivers to overextrapolate reported returns.

Also, our approach provides a fundamentally new *social* explanation for several of the abovementioned empirical findings. For example, the attraction of investors to lottery stocks has uniformly been regarded in past literature as a consequence of nonstandard inherent individual preferences (Brunnermeier and Parker 2005; Barberis and Huang 2008). We show that this is just one possibility. Bias in the social transmission process provides an alternative explanation—one with the distinctive empirical implication that this is intensified by social interactions. Similarly, we provide a social explanation for the attraction of individual investors to idiosyncratic volatility, and further predict that this is intensified by other empirically measurable characteristics of the sending and receiving functions.

We are not the first to examine bias in the social transmission of behavior. The effects of social interactions on the spread of cultural traits have been analyzed in fields such as anthropology (Henrich and Boyd 1998), zoology (Lachlan, Crooks, and Laland 1998; Dodds and Watts 2005), and social psychology (Cialdini and Goldstein 2004).. Economists have also modelled how cultural evolutionary processes affect ethnic and religious traits, and altruistic preferences (Bisin and Verdier 2000; Bisin and Verdier 2001). The focus here is on understanding investment and risk-taking behavior. Financial models have examined how social interactions affect information aggregation, and potentially can generate financial crises.[8] This paper differs from this literature in examining how *SET* and other social transmission biases affect the evolutionary outcome.

Hong, Kubik, and Stein (2004) provide evidence of social influence in stock market participation. In their motivating model, it is *assumed* that social interaction causes participation, but not nonparticipation, to spread from person to person. It follows that more

[7]See, e.g., Hong, Kubik, and Stein (2004) and Kaustia and Knüpfer (2012) for stock market participation, and Kumar (2009) for preference for high skewness stocks and high volatility stocks.

[8]Such models address how information flows in social networks affect asset markets (DeMarzo, Vayanos, and Zwiebel 2001), crises and herd behavior (Cipriani and Guarino 2002; Cipriani and Guarino 2008), and IPO allocations and pricing (Welch 1992). Brunnermeier (2001) and Hirshleifer and Teoh (2009) review the theory of herding in financial markets. Recent models of social networks explore information acquisition, cost of capital, liquidity, and trading volume (Ozsoylev and Walden 2011; Han and Yang 2013). Burnside, Eichenbaum, and Rebelo (2011) apply an epidemic model to explain booms and busts in the housing market; they do not examine transmission bias in conversation, which is the focus of our paper.

social individuals will participate more. However, the opposite is entirely possible. People who are fearful of the market or believe it is an unsavory gambling casino can spread those attitudes to others. Our paper differs in modeling explicity what kinds of performance information tends to spread and be utilized based on the social psychology underlying such transmission processes, to derive endogenously whether active investing spreads.

Also, in Hong, Kubik, and Stein (2004), it is assumed that more social investors spread and acquire *useful* financial education, so that socials are more sophisticated investors. As such, they are more likely to participate in the stock market but are presumably less likely to choose other active strategies that generate poor average performance. In contrast our approach implies that more social investors will seem to be smart in some ways (participation) but will seem foolish in other ways (e.g., investing in active high-expense mutual funds, day trading, or trying to pick the best IPOs).

2 The Model

2.1 Social Interactions, Timing of Events, and Population Shifts

The Population

We consider a population of N individuals who adopt one of two types of investment strategies, A (Active) and P (Passive), which have different return probability distributions. In each period (generation), a pair of individuals is randomly selected to meet. In each pair, one investor randomly becomes the sender and the other the receiver.[9] The returns of the sender and receiver from their current strategies over the period are realized. The sender reports his return to the receiver with probability $s(R_i)$ for sender of type i, which is increasing in the sender's return. Finally, a receiver who receives a message is transformed into the type of the sender with probability $r(R_i)$, also increasing in the sender's return.

Let N_A be the number of type A in the current period or generation and N'_A be the number in the next generation, and let

$$\begin{aligned} f &\equiv \frac{N_A}{N} \\ f' &\equiv \frac{N'_A}{N}. \end{aligned} \tag{1}$$

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

where f_A denotes the population frequency of type A individuals. The total number of individuals in population, N, is constant over time.

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

When an AA or PP pair is drawn, population frequencies remain unchanged. When A and P meet, with probability s the sender communicates his performance and upon receiving the message, the receiver converts to the type of the sender with probability r. We assume that the sending and receiving functions (s and r) directly depend only on the sender's return, i.e., for given return, they are independent of whether the sender or receiver are A or P. Nevertheless, transformations do depend on which type becomes the sender, as this affects the distribution of the sender's return.

Let $T_{ij}(R_i)$ be the probability that the sender, who is of type $i = A, P$, transforms the receiver, who is of type j, into type i, as a function of the sender's return R_i. The change in f, the frequency of type A individuals, after two individuals meet is

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

where χ is the probability that a mixed pair is drawn,

$$\begin{aligned} \chi &\equiv \left(\frac{N_A}{N}\right)\left(\frac{N - N_A}{N-1}\right) + \left(\frac{N - N_A}{N}\right)\left(\frac{N_A}{N-1}\right) \\ &= \frac{2Nf(1-f)}{(N-1)}. \end{aligned} \tag{3}$$

To derive the transformation probability function, we describe the sending function in more detail in the next subsection, and then describe the receiving function in the subsection that follows.

2.2 Self-Enhancement and the Sending Function

To capture self-enhancing transmission bias, we assume that the probability that the sender of type i sends a message describing the sender's strategy and the experienced return is increasing in the performance of the sender's strategy, R_i, so $s'(R_i) > 0$. Potentially consistent with *SET*, Shiller (1990) provides survey evidence that people talked more about real estate in U.S. cities that have experienced rising real estate prices than those that have

not. A sender may, of course, exaggerate or simply fabricate a story of high return. But if senders do not always fabricate, the probability of sending will still depend upon the actual return, and the reported return will tend to be increasing in the actual return.

We apply a linear version of *SET*,

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

where i is the type of the sender. Since the sending function is type-independent, β and γ have no subscripts. To ensure that $0 \leq s(R_i) \leq 1$, we require that $-(\gamma/\beta) \leq R_i \leq (1-\gamma)/\beta$ with high probability, which can hold under reasonable parameter values for β and γ.

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. A high return encourages a sender to discuss his investments, but senders also prefer to obey conversational norms for responsiveness and against bragging.[10]

The positive slope β of the sending schedule reflects *SET*. Consistent with $\beta > 0$, in a database from a Facebook-style social network for individual investors, Heimer and Simon (2014) report that the frequency with which an investor contacts other traders is increasing in the investor's short-term return. The more tightly bound is the sender's self-esteem or reputation to return performance, the stronger is *SET*, and therefore the higher is β.

The constant γ reflects the *conversability* of the investment choice. When the investment is an attractive topic for conversation the sender raises the topic more often. The sender also raises the topic more often when conversations are more extensive, as occurs when individuals are more sociable (how much they talk and share information with each other). So γ also reflects investor sociability.

2.3 The Receiving Function

For a mixed pair of individuals, consider now the probability that a receiver of type j is 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 from a sender with strong performance are more persuasive than messages from a sender with weak performance, so we assume that $r'(R_i) > 0$. This accommodates

[10] With regard to bragging, reporting favorable information about one's achievements and competence often lead to negative reactions in onlookers when the information is not provided in response to a specific question (Holtgraves and Srull 1989). So owing to conversational norms, in some contexts a sender with high return may not get a graceful chance to raise the topic, and in others even a reluctant sender with poor return will feel pressured to report his performance.

the possibility that receivers have some degree of skepticism about the selection bias in the messages they receive, and about sender lying and exaggeration, so long as such skepticism is not complete.

There is extensive evidence in various contexts that observers do not fully discount for selection biases in the data they observe, a phenomenon called selection neglect.[11] Selection neglect is to be expected when individuals with limited processing power automatically process data in fast intuitive ways rather than taking the effortful cognitive step of adjusting for selection bias.

There is also evidence that investors overweight past performance as an indicator of future performance. One or a few recent observations of the performance of a trading strategy generally convey little information about its future prospects. But investors think otherwise.[12] If a receiver believes that past performance is indicative of strategy value, and does not adequately adjust for *SET* as reflected in the sending function (4), then the receiver will tend to overvalue the sender's strategy. This tends to raise the probability of type switching, which promotes a frothy churning in beliefs from generation to generation.

We further assume that $r''(R_i) \geq 0$, to capture general evidence that extreme news is more salient than moderate news, and therefore is more often noticed and encoded for later retrieval (Fiske 1980), Moskowitz (2004).[13] This assumption is mainly needed for the model's skewness predictions, but also reinforces the variance predictions. When cognitive processing power is limited, a focus on extremes is a useful heuristic, as extreme news tends to be highly informative.

Intuitively, convexity results from overlaying additional attention to extreme values of R_i on an otherwise-linearly-increasing relationship between receptiveness and R_i. High salience of extremes is consistent with the finding that individual investors are net buyers of stocks that experience extreme one-day returns of either sign (Barber and Odean 2008),

[11] See, e.g., Nisbett and Ross (1980) and Brenner, Koehler, and Tversky (1996). Koehler and Mercer (2009) find that mutual fund families advertise their better-performing funds, and that both novice investors and financial professionals suffer from selection neglect. Selection neglect is consistent with representativeness, a general psychological bias discussed below.

[12] Such expectations are consistent with the representativeness heuristic (Tversky and Kahneman 1974), and have been incorporated extensively in financial models (e.g., DeLong et al. (1990), Hong and Stein (1999), Barberis and Shleifer (2003)). There is evidence that investors have extrapolative expectations from experimental markets (Smith, Suchanek, and Williams 1988; Choi, Laibson, and Madrian 2010), as well as surveys of return expectations and field evidence on security and fund investing.

[13] High attention to extremes is consistent with the salience theory of choice under risk of Bordalo, Gennaioli, and Shleifer (2012, 2013), wherein individuals' attention focuses upon atypical payoffs, and with the sparsity-based model of Gabaix (2014), wherein individuals construct a simplified model of the world by focusing on the values of few relatively salient variables.

and the finding that extreme gains or losses at other time horizons are associated with higher probability of both selling and of buying additional shares of stocks that investors currently hold (Strahilevitz, Odean, and Barber 2011; Ben-David and Hirshleifer 2012).

We apply a quadratic version of these assumptions,

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

under appropriate parameter constraints ensuring with probability close to 1, r is monotonic and takes value between 0 and 1.

The parameter c measures the susceptibility of receivers to influence, deliberate or otherwise, of the sender's report. The parameter b reflects the degree to which the receiver tends to naively extrapolate past strategy returns, or at least to be persuaded by high returns. The quadratic parameter a reflects the tendency, after allowing for the effect of b, for extreme returns to be more persuasive.[14]

2.4 Transformation Probabilities

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

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

where

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

Similarly,

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

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

[14] Our specification assumes that the probability that the receiver is converted is smoothly increasing in the sender return, and is positive even when the sender has a negative return. One reason for this is that the sheer fact that another individual has adopted or recommends a trading strategy can make an investor aware of the strategy, and can persuade in favor of it. Furthermore, the receiver may have experienced an even lower return on the receiver's current strategy. As a robustness check on our results, in Subsection 2.7.3 we verify that similar results apply in a setting where the switch decision depends on the difference in return between sender and receiver.

2.5 Evolution of Types Conditional on Realized Return

We first show that, owing to *SET*, high return favors active investing. We examine how active return affects both the expected net shift in the fraction of As, which reflects both inflows and outflows, and the expected unidirectional rate of conversion of passives to actives, such as the rate at which investors who have never participated in the stock market start to participate.

Given returns R_P and R_A, we can calculate the expected change in the fraction of type A in the population after one social interaction between two randomly selected individuals. In the four possible pairing AA, PP, AP, or PA (the first letter denotes the sender, the second the receiver), the change in the frequency of type A given AA or PP is zero. The expected changes in the frequency of type A given a meeting AP or PA and realized returns are

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

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

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

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

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

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

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

Since R_A affects T_{AP} but not T_{PA}, these formulas describe how active return affects both the expected net shift in the fraction of As, and the expected unidirectional rate of conversion from P to A.

Furthermore, substituting for the sending function $s(R_A)$ from (4) and the receiving function $r(R_A)$ from (5) into (11) and (12) gives

$$\left(\frac{2N}{\chi}\right)\frac{\partial E[\Delta f|R_A,R_P]}{\partial R_A} = (2aR_A+b)(\beta R_A+\gamma)+\beta(aR_A^2+bR_A+c) \quad (13)$$

$$\left(\frac{2N}{\chi}\right)\frac{\partial^2 E[\Delta f|R_A,R_P]}{\partial (R_A)^2} = 2a(\beta R_A+\gamma)+2\beta(2aR_A+b). \quad (14)$$

Bearing in mind that the sending and receiving functions and their first and second derivatives are all positive (which signs some of the terms in parentheses), it follows immediately from (13) that the sensitivity of the transformation rate of investors to A as a function of past active return is increasing with the parameters of the sending and receiving functions (β, γ, a, b, c). By (14), a similar point follows immediately for convexity as well, with the exception that c does not enter into convexity.

Proposition 1 *Suppose that the returns to A and P are not perfectly correlated. Then:*

1. *The one-way expected rate of transformation from P to A and the expected change in frequency of A are increasing in return R_A.*

2. *These relationships are convex.*

3. *The sensitivity of the expected transformation rate of investors to active investing as a function of past active return, and the convexity of this relationship, are increasing with SET as reflected in β, sociability as reflected in γ, attention of receivers to extremes as reflected in a, and the extrapolativeness of receivers b.*

4. *The sensitivity of the expected transformation rate of investors to active investing as a function of past active return (but not the convexity of this relationship) is increasing with the susceptibility of receivers c.*

This is a rich set of empirical implications, many as yet untested. Items 2-4 are distinctive to our model. For example, since past literature has provided empirical proxies for sociability, it would be interesting to test whether greater sociability is associated with greater slope and convexity of the transformation of investors to active investing as a function of past returns on active strategies. It would also be interesting to test for the effects of variation in *SET* as reflected in β, which could be measured using psychometric testing, or exploit findings from cross-cultural psychology to test for differences in investment behaviors across countries or ethnic groups.

Some important existing evidence is consistent with the first two empirical predictions. Chevalier and Ellison (1997) and Sirri and Tufano (1998) find that investor funds flow into mutual funds with better performance. This is a non-obvious effect since evidence of persistence in fund performance is very limited. Furthermore, the flow-performance relationship is convex; flows are disproportionately into the best-performing funds.

Lu (2011) finds that 401(k) plan participants place a greater share of their retirement portfolios in risky investments (equity rather than fixed income) when their coworkers earned higher equity returns in the preceding period. Kaustia and Knüpfer (2012) report a strong relation between returns and new participation in the stock market in Finland in the range of positive returns. Specifically, in this range, a higher monthly return on the aggregate portfolio of stocks held by individuals in a zip code neighborhood is associated with increased stock market participation by potential new investors living in that neighborhood during the next month.[15] Also, Kaustia and Knüpfer (2012) find evidence supporting a prediction of Part 3 in Proposition 1 that the sensitivity of the one-way expected rate of transformation from P to A (stock market entry in their setting) increases with the intensity of social interaction.

The greater strength of the effect in the positive range is consistent with the convexity prediction. Furthermore, within the positive range the effect is stronger for higher returns. Our model does not imply a literally zero effect in the negative range, but a weaker effect within this range (as predicted by Proposition 1) would be statistically harder to detect.

Kaustia and Knupfer explain their basic finding—that higher returns convert more nonparticipants to enter the market—based on what we call *SET*, together with overextrapolation of others past returns. Part 1 of Proposition 1 captures *SET* by $s'(R_A) > 0$, and the greater willingness of receivers to convert when return is higher by $r'(R_A) > 0$.

Furthermore, Part 2 of the proposition delivers a more subtle effect, the convexity of the conversion/return relation. This effect arises naturally from the interaction of sending and receiving functions in our model. By (11), $s' > 0$ and $r' > 0$ together contribute to convexity of expected transformation as a function of R_A. Intuitively, multiplying two increasing functions generates rising marginal effects as the argument increases. A further contributor is the convexity of the receiver function, $r''(R_A)$, reflecting high salience of extreme outcomes.[16]

[15] Their test focuses on the conversion of new investors to stock market investing, i.e., the conversion of Ps to As. They do not test predictions in Proposition 1 about change in net shift from P to A, which accounts for possible shifts from A to P as well.

[16] An examination of (13) and (14) clarifies the drivers of the basic findings (Parts 1 and 2). Part 1 holds even without *SET* (i.e., even if $\beta = 0$). Intuitively, a higher return is simply more persuasive to

If we interpret A as active trading in the market for individual stocks, with a preponderance of long positions, then a high market return implies high average returns to A investors. Proposition 1 therefore implies that when the stock market rises, volume of trade in individual stocks increases. This implication is consistent with episodes such as the rise of day trading, investment clubs, and stock market chat rooms during the millennial internet boom, and with evidence from 46 countries including the U.S. that investors trade more when the stock market has performed well (Statman, Thorley, and Vorkink 2006; Griffin, Nardari, and Stulz 2007). In Appendix D, we formally model market equilibrium with trading volume to verify that evolution toward A is associated with high trading volume.

2.6 Strategy Return Components and the Meaning of Active Investing

We now make exogenous assumptions about the distributions of strategy returns to derive implications about the spread of active investing. This partial equilibrium approach lets us interpret 'active investing' broadly as referring either to static actions such as holding a given risky asset, or to dynamic strategies such as day trading, margin investing, stock picking, market timing, sector rotation, dollar cost averaging, technical analysis, and so forth. In Section 3, to derive implications for equilibrium trading and prices, we model A more specifically as placing a higher valuation than P upon a risky asset, and solve for equilibrium expected returns of A and P. The advantage of the partial equilibrium approach is that it permits a broader interpretation of A versus P, and that its milder assumptions allow us to analyze simply the effects of return skewness.

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

$$\begin{aligned} R_A &= \beta_A r + \epsilon_A - D \\ R_P &= \beta_P r + \epsilon_P, \end{aligned} \tag{15}$$

where β_i is the sensitivity of strategy return to the common return component. We assume

receivers, which causes conversion. *SET* provides another channel for the prediction in Part 1 by causing sending to increase after positive returns. For Part 2, attention to extremes ($a > 0$) promotes convexity, because as past returns increase, at first the marginal effect is weak (because of lack of attention to very low returns), and then becomes stronger (because of increasing attention to very high returns). But attention to extremes is not required for convexity. Even if $a = 0$, *SET* induces convexity, because when $\beta > 0$, the persuasive effect of higher return on receivers is reinforced multiplicatively by a stronger tendency of senders to send.

that the active strategy has higher systematic risk, $\beta_A > \beta_P \geq 0$. We further assume that $\sigma_A^2 > \sigma_P^2$, $\gamma_{1A} > 0$, $\gamma_{1P} \approx 0$, and $\gamma_{1r} \geq 0$, where σ_A^2, σ_P^2 are the variances of ϵ_A and ϵ_P, γ_{1r} is the skewness of r, and γ_{1A}, γ_{1P} are the skewnesses of ϵ_A and ϵ_P. We also let σ_r denote standard deviation of the common factor r.

To summarize these conditions, active investing means choosing strategies with return distributions that have higher volatility and possibly also higher skewness. This corresponds fairly well with common parlance, but there are possible exceptions. For example, a long-short strategy that achieved low risk, or a dynamic hedging strategy using a stock and its option that is used to generate a riskfree payoff would not be active in the sense we are using.

Since $E[r] = E[\epsilon_i] = 0$, (15) implies that $E[R_P] = 0$, 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 welfare loss may come from lack of diversification and excessive idiosyncratic risk-bearing. So even if $D < 0$, the As may be worse off than Ps.[17]

In a setting that explicitly models trading decisions and equilibrium price-setting, risk premia and mispricing would affect $E[R_A]$ and $E[R_P]$. The difference in expected returns between the two strategies $E[R_A] - E[R_P]$ in general varies over time as a function of the fraction of type A investors. A rise in A in the population tends to be self-limiting, because a higher frequency of A tend to move prices against active strategies. The reduction in the expected value to A relative to P would be reflected here by a higher expected return differential D. So in an equilibrium setting we expect, apart from random fluctuations, a balanced frequency of A and P between zero and one. We evaluate these intuitions in Section 3.

2.7 Unconditional Expected Evolution of Types

Since the r and s functions are type-independent and the only random variable they depend upon is the sender return, in expectation the spread of A versus P derives from the effect

[17] Also, since $E[r] = 0$, the model only implicitly captures factor risk premia through the possibility of a negative D; this expected return advantage to A is not a welfare advantage. Even when $D < 0$, if As overvalue the risky asset and Ps are rational, being an A rather than a P *decreases* an individual's true expected utility (owing to excessive risk-taking, and an insufficient reward for bearing risk). So the return penalty to active trading D underestimates the welfare loss from active trading. Greater transaction costs of active trading (not modeled here) would also be reflected in D. There is evidence that U.S. and Taiwan investors underperform in their individual stock trades (Barber and Odean (2000b), Barber et al. (2009)), but that active individual fund investors in Sweden outperform passive investors (Dahlquist, Martinez, and Söderlind 2012).

of A versus P on the distribution of sender returns R, as reflected in mean, variance, and skewness.

To see how the population evolves unconditionally after one meeting, we take the expectation of the change in the population fraction of A over R_A and R_P in (10):

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

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

By (15) and direct calculation,

$$\begin{aligned} T_{AP}(R_A) - T_{PA}(R_P) &= a\beta\left(R_A^3 - R_P^3\right) + B\left(R_A^2 - R_P^2\right) + C(R_A - R_P) \\ &= a\beta[(\beta_A^3 - \beta_P^3)r^3 + 3r^2(\beta_A^2\epsilon_A - \beta_P^2\epsilon_P) + 3r(\beta_A\epsilon_A^2 - \beta_P\epsilon_P^2) + \epsilon_A^3 - \epsilon_P^3] \\ &\quad + B[(\beta_A^2 - \beta_P^2)r^2 + 2r(\beta_A\epsilon_A - \beta_P\epsilon_P) + \epsilon_A^2 - \epsilon_P^2] + C[(\beta_A - \beta_P)r + \epsilon_A - \epsilon_P] \\ &\quad + D\{-(r\beta_A + \epsilon_A)[3a\beta(r\beta_A + \epsilon_A) + 2B] - C\} + D^2[3a\beta(r\beta_A + \epsilon_A) + B] \\ &\quad - aD^3\beta. \end{aligned} \tag{17}$$

Taking the expectation over r, ϵ_A and ϵ_P, the expected change in frequency satisfies

$$\begin{aligned} \left(\frac{2N}{\chi}\right) E[\Delta f] &= E[T_{AP}(R_A) - T_{PA}(R_P)] \\ &= a\beta[(\beta_A^3 - \beta_P^3)\gamma_{1r}\sigma_r^3 + \gamma_{1A}\sigma_A^3 - \gamma_{1P}\sigma_P^3] + \; B[(\beta_A^2 - \beta_P^2)\sigma_r^2 + (\sigma_A^2 - \sigma_P^2)] \\ &\quad + Da\beta(-3\sigma_A^2 - D^2 - 3\sigma_r^2\beta_A^2) + D^2B - DC, \end{aligned} \tag{18}$$

recalling that σ denotes standard deviation and $\gamma_{1\cdot}$ denotes skewness.

2.7.1 Comparative Statics

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

Proposition 2 *If $D \approx 0$, then under the parameter constraints of the model, the per-meeting expected change in the fraction of A, $E[\Delta f]$:*

1. *Decreases with the return penalty to active trading D;*
2. *(a) Increases with factor skewness, γ_{1r};*
   (b) Increases with active idiosyncratic skewness, γ_{1A};
3. *(a) Increases with active idiosyncratic volatility, σ_A;*

(b) *Increases with the factor loading of the active strategy, β_A;*

(c) *Increases with the variance of the common factor, σ_r^2;*

4. *Increases with SET, β;*

5. *Increases with the extrapolativeness of receivers, b;*

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

7. *Increases with the conversability, γ, of trading strategies. If $D > 0$ sufficiently large, then the expected rate of increase in the fraction of A decreases with the conversability;*

8. *Can either increase or decrease with the susceptibility of receivers, c; the relation is increasing when $D < 0$ and decreasing if $D > 0$.*

If we view A as the choice of investments motivated by overoptimism about certain stocks, then the predictions in Proposition 2 about the frequency of A become predictions that the trading strategies adopted by A become overpriced. So from an equilibrium perspective, the evolution toward A depresses the expected returns of risky assets. In discussing the partial equilibrium comparative statics predictions about the frequency of A, we will make use of this equilibrium intuition to draw predictions about expected returns.

Part 1 makes the fairly obvious point that if the average return penalty D to active trading is larger, A will be less successful in spreading through the population.[18]

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

$$\begin{aligned} \left(\frac{2N}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \gamma_{1r}} &= a\beta\sigma_r^3(\beta_A^3 - \beta_P^3) \\ &> 0, \end{aligned} \tag{19}$$

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, to be noticed, and to convert the receiver when noticed. Since A has a greater factor loading than P, factor skewness is magnified in A relative to P, making A more contagious.

[18] To show Part 1, we differentiate (18) with respect to D to obtain that if $D < 0$ or D is positive but not too large,

$$\left(\frac{2N}{\chi}\right)\frac{\partial E[\Delta f]}{\partial D} = -3a\beta(\beta_A^2\sigma_r^2 + \sigma_A^2) + D(-3aD\beta + 2B) - C < 0.$$

The ambiguity for large D results from a spurious effect: for sufficiently large negative R, the slope of the quadratic receiving function turns negative. In consequence, a larger return penalty to active trading, D, can, perversely, help convert Ps to As by inducing larger losses.

For Part 2b, differentiating with respect to active idiosyncratic skewness γ_{1A} gives

$$\begin{aligned} \left(\frac{2N}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \gamma_{1A}} &= a\beta\sigma_A^3 \\ &> 0. \end{aligned} \tag{20}$$

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

Part 2b implies that conversation especially encourages demand for securities with high skewness. Mitton and Vorkink (2007) and Goetzmann and Kumar (2008) document that underdiversified individual investors (presumably naive investors—whom we would expect to be most subject to social influence) tend to choose stocks with high skewness—especially idiosyncratic skewness. In addition, the effect of skewness in Parts 2a and 2b increases with the salience of extreme returns, a (see (19) and (20)). Barber and Odean (2008) find that individual investors are net buyers of stocks following extreme price moves, but that institutional investors behave in opposite fashion. So if naive individual investors are more affected by the salience of extreme returns, this would reinforce the attraction of individual investors to high skewness.

Examples of skewed securities include options, and 'lottery stocks', such as real option firms that have a small chance of a jackpot outcome. Consistent with investors favoring positively skewed stocks, ex ante return skewness is a negative predictor of future stock returns (Conrad, Dittmar, and Ghysels 2013; Eraker and Ready 2014). There is also evidence from initial public offerings (Green and Hwang 2012) and general samples (Bali, Cakici, and Whitelaw 2011) that lottery stocks are overpriced, and that being distressed (a characteristic that leads to a lottery payoff distribution) on average predicts negative abnormal returns (Campbell, Hilscher, and Szilagyi 2008). Boyer and Vorkink (2011) find that the ex ante skewness of equity options is a negative cross-sectional predictor of option abnormal returns.

Existing explanations of the tendency of individual investors to favor lottery stocks are based on non-traditional preferences (Brunnermeier and Parker 2005; Barberis and Huang 2008). In Brunnermeier and Parker (2005), agents who optimize over beliefs prefer skewed payoff distributions. In Barberis and Huang (2008), prospect theory preferences with probability weighting creates a preference over portfolio skewness, which induces a demand for 'lottery' (high idiosyncratic skewness) stocks that contribute to portfolio skewness.

These theories are highly plausible, but there are indications that the tendency to favor lottery stocks does not derive solely from hard-wired psychological biases. Consistent

with a possible effect of social contagion, individuals who live in urban areas buy lottery tickets more frequently than individuals who live in rural areas (Kallick et al. (1979)). Furthermore, there is evidence suggesting that the preference for high skewness stocks is greater among urban investors, after controlling for demographic, geographic, and personal investing characteristics (Kumar 2009).[19]

Furthermore, investment in lottery-type stocks depends on the socioeconomic environment such as religion (Kumar 2009), a cultural trait that is adopted through social interaction. Our approach offers a different pathway by which social interaction affects lottery choices—one that involves direct adoption of investment strategies rather than the lower-frequency social transmission of religious beliefs.

A key difference of our approach from approaches based upon inherent preferences over beliefs or over portfolio skewness is that biases in the transmission process cause the purchase of lottery stocks to be contagious. This can help explain the empirical association of high social interaction with gambling and lottery behaviors. In our setting, greater social interaction increases contagion, thereby increasing the holdings of lottery stocks.[20] For example, individuals with greater social connection (as proxied, for example, by population density, participation in investment clubs, or self-reports of interactions with neighbors or regular church-going) will favor such investments more.

For Part 3a, differentiating with respect to active idiosyncratic volatility σ_A gives

$$\begin{aligned} \left(\frac{2N}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \sigma_A} &= 3a\beta\gamma_{1A}\sigma_A^2 + 2(B - 3aD\beta)\sigma_A \\ &> 0 \end{aligned} \tag{21}$$

if $D \approx 0$ or $D < 0$. Thus, if D is sufficiently small, the growth of A increases with active idiosyncratic volatility σ_A. Greater return variance increases the effect of SET on the part of the sender. Although high salience to receivers of extreme returns ($a > 0$) is not required for the result, it reinforces this effect. Indeed, even if there were no SET ($\beta = 0$), since $a > 0$ implies that $B > 0$, the result would still hold. Intuitively, high volatility generates the extreme outcomes which receive high attention.

Consistent with Part 3a, Goetzmann and Kumar (2008) document that underdiversified investors prefer stocks that are more volatile. A further empirical implication of Part

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

[20]In particular, when A means higher skewness, we find that having social interaction results in the spread of A, i.e., $E[\Delta f] > 0$, whereas if there were no social interaction we would have $E[\Delta f] = 0$. Alternatively, if greater social interaction is interpreted to mean more frequent meetings in calendar time, then positive expected change in f that derives from positive skewness is realized more often per unit time.

3a is that in periods in which individual stocks have high idiosyncratic volatility, all else equal there will be greater holding of and volume of trade in individual stocks. Intuitively, during such periods As have higher returns to report selectively. This implication is in sharp contrast with the prediction of portfolio theory, which suggests that in periods of high idiosyncratic volatility, the gains to holding a diversified portfolio rather than trading individual stocks is especially large. Tests of this prediction, especially if a shift in idiosyncratic volatility can be attributed to fundamentals, would therefore distinguish competing theories.

The idiosyncratic volatility puzzle is the finding that stocks with high idiosyncratic risk earn low subsequent returns (Ang et al. (2006, 2009)). This apparent overpricing is stronger for firms held more heavily by retail investors (Jiang, Xu, and Yao 2009; Han and Kumar 2013), for whom we would expect conversational biases to be strong. Thus, the theory offers a possible *social* explanation for the idiosyncratic volatility puzzle: the high returns generated by volatile stocks are heavily discussed, which increases the demand for such stocks, driving up their prices.

A plausible individual-level explanation for these findings is that realization utility or prospect theory with probability weighting creates a preference for volatile portfolios and stocks (Barberis and Huang 2008; Boyer, Mitton, and Vorkink 2010). However, a distinctive aspect of our explanation is that the effect derives from social interaction. Consistent with social contagion playing a role, in tests using extensive controls, the preference for high volatility is greater among urban investors (Kumar (2009); see also footnote 19).

For Part 3b, differentiating with respect to the factor loading of the active strategy, β_A, gives

$$\begin{aligned} \left(\frac{2N}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \beta_A} &= 3a\beta\beta_A^2\gamma_{1r}\sigma_r^3 + 2\beta_A\sigma_r^2 B - 6a\beta\beta_A\sigma_r^2 D \\ &> 0 \end{aligned} \tag{22}$$

if $D < 0$ or $D \approx 0$. So a greater factor loading for A increases the spread of A, since the greater dispersion of return outcomes encourages the sending of high, influential messages.

Baker, Bradley, and Wurgler (2011) report that in the U.S., high beta stocks have substantially underperformed low beta stocks over the past 41 years; Frazzini and Pedersen (2014) also find that high beta stocks underperform and low beta stocks overperform. Frazzini and Pedersen (2014) propose a rational explanation of this effect based on borrowing constraints. However, Bali et al. (2015) provide evidence favoring a behavioral explanation based on naive demand for stock with lottery characteristics. They also document that the

betting against beta effect occurs only in stocks with low levels of institutional ownership, a relatively naive investor base. This is consistent with our approach, since we expect naive investors to be more subject to *SET* (as reflected in β), and the comparative statics in (22) is stronger for larger β.

For Part 3c, differentiating with respect to the variance of the common factor, σ_r^2 gives

$$\begin{aligned}\left(\frac{2N}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \sigma_r^2} &= 1.5a\beta(\beta_A^3-\beta_P^3)\gamma_{1r}\sigma_r + B(\beta_A^2-\beta_P^2) - 3Da\beta\beta_A^2 \\ &> 0 \end{aligned} \tag{23}$$

if $D < 0$ or $D \approx 0$. So greater volatility of the common factor favors the spread of A. Greater factor volatility outcomes encourages the spread of the strategy with the greater loading, A, by creating greater scope for *SET* to operate.

This implies that other things being equal, there will be greater stock market participation in time periods and countries with more volatile stock markets. This contrasts with the conventional theory, in which greater risk, *ceteris paribus* reduces the benefit to participation.

Overall, the findings on factor loadings and the different components of volatility (Parts 3a, 3b, and 3c) suggest that volatility will be overvalued in the economy. As such, the model does not offer any help in explaining the equity premium puzzle—the high returns on the U.S. equity market. Of course, there are other possible explanations for the equity premium.

A distinctive set of empirical implications pertaining to these volatility-related comparative statics is that the effect will be intensified by greater sociability as reflected in γ (which enters positively in B in equations (21), (22), and (23)), and by other characteristics of the sending and receiving functions such as salience of extreme returns as reflected in a, *SET* as reflected in β, and the extrapolativeness of receivers as reflected in b. Such parameters are empirically measurable. For example, Barber and Odean (2008) estimate the effects of investor attention to extreme returns, and several papers estimate the extrapolativeness of return expectations using both survey approaches (Case and Shiller 1988; DeBondt 1993; Vissing-Jorgensen 2003) and field evidence (Greenwood and Shleifer 2014; Hoffmann and Post 2015).

For Part 4, we differentiate with respect to β, the strength of *SET*. This reflects how tight the link is between the sender's self-esteem and performance. Recalling by (7) that

B is an increasing function of β, gives

$$\begin{aligned}\left(\frac{2N}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \beta} &= a(\gamma_{1A}\sigma_A^3 - \gamma_{1P}\sigma_P^3) + a\sigma_r^3(\beta_A^3 - \beta_P^3)\gamma_{1r} + b[(\beta_A^2 - \beta_P^2)\sigma_r^2 + \sigma_A^2 - \sigma_P^2] \\ &\quad + Da(-3\sigma_A^2 - 3\beta_A^2\sigma_r^2 - D^2) + D^2 b - Dc \\ &> 0 \end{aligned} \tag{24}$$

if $D \approx 0$ or $D < 0$. So greater *SET* increases the evolution toward A, because *SET* causes greater reporting of the high returns that make A enticing for receivers. A generates extreme returns for *SET* to operate upon through higher factor loading, idiosyncratic volatility, or more positive idiosyncratic skewness.

For Part 5, differentiating with respect to the tendency of receivers to extrapolate returns, b, gives

$$\begin{aligned}\left(\frac{2N}{\chi}\right)\frac{\partial E[\Delta f]}{\partial b} &= \beta[(\beta_A^2 - \beta_P^2)\sigma_r^2 + \sigma_A^2 - \sigma_P^2] + D(D\beta - \gamma) \\ &> 0 \end{aligned} \tag{25}$$

if $D \approx 0$ or $D < 0$. Greater extrapolativeness of receivers helps A spread by magnifying the effect of *SET* (reflected in β), which spreads A because of the higher volatility of A returns. The analysis therefore implies, for example, that active investing will be more popular when extrapolative beliefs are stronger (past returns are perceived to be more informative about the future); as mentioned above, extrapolativeness can be estimated empirically to test this hypothesis.

For Part 6, 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

$$\begin{aligned}\left(\frac{2N}{\chi}\right)\frac{\partial E[\Delta f]}{\partial a} &= \beta\sigma_r^3\gamma_{1r}(\beta_A^3 - \beta_P^3) + \beta[\gamma_{1A}\sigma_A^3 - \gamma_{1P}\sigma_P^3] + \gamma[(\beta_A^2 - \beta_P^2)\sigma_r^2 + \sigma_A^2 - \sigma_P^2] \\ &\quad - 3D\beta(\beta_A^2\sigma_r^2 + \sigma_A^2) + D^2\gamma - D^3\beta \\ &> 0 \end{aligned} \tag{26}$$

if $D \approx 0$ or $D < 0$. So greater attention by receivers to extreme outcomes, a, promotes the spread of A over P because A generates more of the extreme returns which, when a is high, are especially noticed and more likely to persuade receivers. This effect is reinforced by *SET*, which causes greater reporting of extreme high returns.

For Part 7, differentiating with respect to conversability γ gives

$$\begin{aligned}\left(\frac{2N}{\chi}\right)\frac{\partial E[\Delta f]}{\partial \gamma} &= a[(\beta_A^2-\beta_P^2)\sigma_r^2+\sigma_A^2-\sigma_P^2]-bD+aD^2 \\ &> 0 \end{aligned} \tag{27}$$

if $D \approx 0$ or if $D < 0$. Greater conversability γ can help the active strategy spread because of the greater attention paid by receivers to extreme returns ($a > 0$), which are more often generated by the A strategy. When $D < 0$, this effect is reinforced by the higher mean return of A. In this case an unconditional increase in the propensity to report returns tends to promote the spread of the sender's type more when the sender is A. On the other hand, if $D > 0$ is sufficiently large, A earns lower return than P on average, so greater conversability incrementally produces more reporting of lower returns when the sender is A than P, which opposes the spread of A.

If expected returns of A and P are similar or the expected return of A is higher, the effect of extreme returns dominates, so higher γ tends to promote A. This case is consistent with the idea that active trading will tend to become more popular when people become more talkative about their investment performance. Examples include the rise of communication technologies, media, and such social phenomena as ubiquitous computing, stock market chat rooms, investment clubs, and blogging. This raises the possibility that the rise of these phenomena (if taken to be exogenous) may have contributed to the internet bubble.

Also, trading outcomes are a trigger for conversation about trading, so over time as markets become more liquid and trading becomes more frequent, we expect conversation about outcomes to become more frequent. The trend toward greater availability of real-time reporting and discussion of financial markets on television and through the internet therefore can induce more rapid evolution toward more active investing.

If greater general sociability is associated with greater comfort in discussing performance information, then in any given conversation it increases the unconditional probability that the sender will discuss returns; i.e., it increases γ. So again, if the expected return of A is not too low, this will increase evolution toward active trading. Empirically, participation in online communities has been found to be associated with riskier financial decisions (Zhu et al. (2012)). Using field studies, the authors found greater risk-taking in bidding decisions and lending decisions by participants in discussion forums (Prosper.com) and in discussion boards and chat rooms (eBay.de), and that risk-taking increases with how active the participants are in the community.

There is also survey evidence that sociability is associated with greater stock market participation (Hong, Kubik, and Stein 2004). Similarly, survey evidence from ten European

countries indicates that household involvement in social activities is associated with greater stock market participation (Georgarakos and Pasini 2011). Furthermore, Heimer (2014) documents that social interaction is more prevalent amongst active investors who buy and/or sell stocks than passive investors who hold U.S. savings bonds, thereby supporting our explanation for the active investing puzzle in which informal communication tends to promote active rather than passive strategies.

As discussed earlier, another reasonable way to interpret the active versus passive distinction is that active strategies are more conversable (less conventional, more affect-triggering, or more arousing). (As documented by Berger and Milkman (2012), more arousing online content is more viral.) This distinction could be incorporated formally by replacing γ in the sending function with γ_A and γ_P, where $\gamma_A > \gamma_P$. However, the model generates a survival advantage for A even without a conversability advantage. It is immediately evident that $\gamma_A > \gamma_P$ favors the spread of A, since a receiver cannot be converted unless he receives a message from the sender. Intuitively, $\gamma_A > \gamma_P$, *ceteris paribus*, causes adopters of A to evangelize to Ps more often than the other way of around, which favors evolution of the population toward A. So we simply assert this conclusion while maintaining the simplicity of a single γ for the remaining analysis.

With $\gamma_A > \gamma_P$, the model further implies that there will be overvaluation of stocks with 'glamour' characteristics that make them attractive topics of conversation, such as growth, recent IPO, sports, entertainment, media, and innovative consumer products (on growth, see Lakonishok, Shleifer, and Vishny (1994); underperformance of IPO and small growth firms, see Loughran and Ritter (1995) and Fama and French (1993)). In contrast, there will be neglect and underpricing of unglamourous firms that are less attractive topics of conversation, such as business-to-business vendors or suppliers of infrastructure. Conversational transmission biases can therefore help explain several well known empirical puzzles about investor trading and asset pricing.

Related predictions about the effects of investor attention have been made before (Merton 1987). A distinctive feature of our theory is that the effects derive from social interaction, and should therefore be stronger in times and places with stronger interactions. This point provides additional empirical predictions about the effects on trading and return anomalies of population density, urban versus rural localities, pre- and post-internet periods, differences in self-reported degrees of social engagement, popularity of investment clubs and chat rooms, and so forth.

Lastly, for Part 8 of the Proposition, differentiating with respect to the susceptibility of receivers c gives

$$\begin{aligned} \left(\frac{2N}{\chi}\right)\frac{\partial E[\Delta f]}{\partial c} &= -D\beta \\ &> 0 \end{aligned} \tag{28}$$

if $D < 0$; the inequality is reversed if $D > 0$. Greater susceptibility increases the likelihood that the receiver is transformed *given that* the sender sends. Owing to *SET* (as reflected in the β term above) the probability that A sends is increased relative to the probability that P sends when the returns of A are higher, i.e., $D < 0$. This condition will hold if there is a risk premium for the active strategy, even if the premium is not fully commensurate with the risk. An implication of this is that when there are stronger pressures toward conformity (hence, more susceptible receivers), there is a stronger tendency for the culture to evolve toward A.

The comparative statics of Proposition 2 describe the effects of parameter shifts on the expected shift in the fraction of As in the next period. In Subsection 2.8 we derive similar comparative statics implications for the population dynamics over time, rather than just the expected change over the next time period.

2.7.2 The Evolutionary Success of Active Investing

The intuitions underlying the comparative statics of Proposition 2 provide insight about the extent to which, overall, evolution favors A or P. The next proposition follows immediately by (18) and the parameter constraints of the model ($\beta_A > \beta_P \geq 0$, $\sigma_A^2 > \sigma_P^2$, $\gamma_{1A} > 0$, $\gamma_{1P} \approx 0$, and $\gamma_{1r} \geq 0$).

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 reinforcing effects. Based on the previous comparative statics, owing to *SET*, the spread of A over P is favored by its higher factor loading β_i, idiosyncratic skewness γ_{1i}, and idiosyncratic volatility σ_i. A strategy that is more volatile (either because of greater loading on a factor or because of idiosyncratic risk) magnifies the effect of *SET* in persuading receivers to the strategy. Owing to greater attention to extremes ($a > 0$), skewness (which generates salient and influenti high returns) further reinforces the success of A, but *SET* promotes the spread of A even if $a = 0$.

An additional direct effect which does not rely on *SET* further promotes the success of A. This further effect only operates if $a > 0$ (salience of extreme news). Starting as benchmark with the case of $a = 0$, in the absence of *SET* ($\beta = 0$), and if the expected returns of the two strategies are the same, the transformation of P investors to A resulting from overextrapolation by receivers of high A returns is exactly offset by transformations in the other direction when returns are low. So the expected change in the fraction of active investors from a meeting is zero.[21]

However, if $a > 0$, the receiving function is convex, so that high returns have a stronger effect on the upside than low returns have on the downside. Owing to the higher variance of A, it generates extreme returns more often, which intensifies this favorable effect.

To see this algebraically, eliminate *SET* in the model by setting $\beta = 0$. Then the expected change in frequency of A is, up to a multiplicative constant,

$$E[T_{AP}(R_A) - T_{PA}(R_P)] \quad = \quad a\gamma[(\beta_A^2 - \beta_P^2)\sigma_r^2 + (\sigma_A^2 - \sigma_P^2)] - Db\gamma. \tag{29}$$

Setting aside the mean return term $Db\gamma$, we see that even without *SET*, there tends to be growth in the frequency of A if there is attention to extremes ($a > 0$). However, there is no inherent tendency for high skewness strategies to spread. This can also be seen from the comparatives statics of equations (19)-(20), in which the effects of skewness are eliminated when $\beta = 0$.

In summary, *SET* promotes A owing to its higher variance and (if $a > 0$), its higher skewness; the attention to extremes effect (combined with extrapolation) promotes A only when $a > 0$, and only via a variance effect, not a skewness effect.

Individual investors are probably relatively strongly influenced by social interactions rather than independent analysis and investigation. This suggests that the predictions of Propositions 2 and 3 that social interaction favors active investing will apply more strongly to individual investors than to professionals.

2.7.3 An Alternative Specification for the Receiving Function

We have assumed throughout that a receiver is influenced only by the sender's return, not own return. This assumption may seem unrealistic, but should matter little for qualitative conclusions, as each type has an equal chance of becoming the sender.

[21] More generally, when expectations are extrapolative, whichever strategy has higher mean return will, all else equal, tend to spread owing to the persuasiveness of higher returns. However, in an equilibrium setting, growing popularity is self-limiting, as it drives the price of the A strategy up and its expected return down.

As a robustness check, we examine here an alternative specification where the receiving function depends on the difference between the returns of the sender and the receiver. Specifically, we now assume that when a sender of type A meets with a receiver of type P and communicates return R_A, P is converted to type A with probability $r_{AP}(R_A) = a(R_A - R_P)^2 + b(R_A - R_P) + c$. We have verified that Propositions 1, 2 (except for Part 7 on the effect of conversability), and Proposition 3 remain valid when the receiving function depends on the return difference between the sender and the receiver.

In the model, investors decide whether to switch strategy based only on the most recent period's return. In principle, fully rational investors could eventually converge to the best action by observing a long history of returns. This could take a long time since strategy return realizations are noisy indicators about which strategy is better. Meanwhile, new investors are continually arriving and experienced investors departing. Our model captures this in an extreme way by allowing investors to retain return messages for only single period. Also, when the sending and the receiving function depend on returns over multiple past periods, as discussed in the concluding section, boom-bust dynamics are possible.

2.8 Implications for Population Dynamics

Proposition 2 provides implications about the expected change in the fraction of active investors over the next transaction. We now study the dynamics over extended time periods of the prevalence of A in the population. In particular, we perform comparative statics for the level of expected frequency of active investors in the population at any given future time.

We maintain the previous model assumptions, with the following modifications. For technical tractability, we assume an infinitely large population of investors to meet over time intervals of arbitrarily short length. Furthermore, we assume that the common factor return follows a standard Gaussian diffusion process. By the law of large numbers, the randomness at the individual level caused by the matching and individual-specific return components average out. Randomness remains, however, owing to the common factor in returns. These assumptions enable us to derive continuous-time dynamics for the frequency of active investors in the population, resulting in the following comparative statics.

The results are stated in the following Proposition, which is proved in Appendix B.

Proposition 4 *Under the parameter constraints of the model (and for Part 5, under the further assumption that $c = 0$), for any given time $t > 0$, the expected population frequency of A, $E[f]$:*

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

2. *Increases with active idiosyncratic skewness, γ_{1A};*

3. *Increases with active idiosyncratic volatility, σ_A;*

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

5. *Increases with SET, β.*

The proof is based upon the nonlinear stochastic differential equation that describes the evolution of f_t in continuous time (see (61) in Appendix B). This resembles (but is more complicated than) the logistic growth equation in population ecology or innovation diffusion in social sciences. An analytical solution for $E[f_t]$ is unavailable, but we are able to apply a stochastic dominance argument to prove comparative statics for the five model parameters in Proposition 4. These are consistent with those of Proposition 2.[22]

3 Equilibrium Trading and Returns

So far, we have viewed active investing as referring to either some static action such as holding a given risky asset, or to a dynamic trading strategy. To explicitly examine market-clearing and derive implications for equilibrium trading and prices, we now specify A as referring to placing a higher valuation than P upon a risky asset.

In the next subsection, we consider the case of a single risky asset. This lays the groundwork for Subsection 3.2, in which there are many risky assets.

3.1 Active and Passive Returns

Consider a riskfree asset and a risky asset, each of which generates a terminal value one period later and liquidates. The riskfree asset is in zero net supply, with return denoted R_F. The risky asset S has a terminal value V which is optimistically perceived by As to have expected value $\overline{V}_A$, and by the Ps to have $\overline{V}_A > \overline{V}_P$. Both types agree about the variance of risky asset return. A new realized terminal value is redrawn independently each period, and investors myopically optimize each period based upon their current beliefs. We

[22]For technical reasons, our proof approach does not apply to the other parameters. But we have verified numerically that the comparative statics of $E[f_t]$ with respect to other model parameters are also similar to those in Proposition 2. To evaluate $E[f_t]$ numerically, we discretize the stochastic differential equation (61), simulate 1,000 paths for the evolution of the fraction of A in the population from time 0 to t, and average the ending values f_t across the simulations.

distinguish agent expectations, denoted by $E_i[-]$ or 'bar' variables with subscripts, from true expectations, denoted by unscripted $E[-]$.

Each period each investor is newly endowed with one unit of the riskfree numeraire to invest fully in the two assets. Upon realization of returns the investor consumes the payoffs of these assets. At this point the old assets vanish, and a new endowment of the numeraire and risky asset appears. Letting w_A and w_P be the portfolio weights (i.e., fraction of wealth) placed by each type on the risky asset, the returns achieved by an A or P are

$$\begin{aligned} R_A &= (1-w_A)R_F + w_A R_S \\ R_P &= (1-w_P)R_F + w_P R_S. \end{aligned} \tag{30}$$

The investors' mean-variance decision problem is

$$\max_{w_i} \quad E_i[R_i] - \left(\frac{\nu}{2}\right) var(R_i), \quad i = A, P, \tag{31}$$

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

Let $\bar{R}_{Si}$ denote the expectation by type i of the return on the risky asset. Substituting for the R_A and R_P from (30) gives the optimization problems

$$\max_{w_i} \quad (1-w_i)R_F + w_i\bar{R}_{Si} - \left(\frac{\nu}{2}\right) w_i^2\sigma_S^2, \quad i = A, P. \tag{32}$$

Differentiating with respect to w_i and solving gives

$$w_i = \frac{\bar{R}_{Si} - R_F}{\nu\sigma_S^2}, \quad i = A, P. \tag{33}$$

So the As, as optimists, invest more in the risky asset. Substituting for the w's in (30) using (33) gives

$$R_A - R_F = \lambda(R_P - R_F), \tag{34}$$

where

$$\lambda \equiv \frac{\bar{R}_{SA} - R_F}{\bar{R}_{SP} - R_F}. \tag{35}$$

So the excess return that an A investor chooses to bear is a leveraged multiple—possibly with a negative coefficient—of the excess returns—possibly negative—borne by the Ps.

It follows by (34) and (35) that

$$\begin{aligned} R_A &= \lambda R_P + (1-\lambda) R_F \\ &= \lambda R_P + (1-\lambda) E[R_P] - D \end{aligned} \tag{36}$$

where by (30),

$$D \stackrel{def}{=} (1-\lambda)(E[R_P] - R_F) = (1-\lambda) w_P (E[R_S] - R_F). \tag{37}$$

Taking the expectation of both sides of (36), we see that D is the expected return penalty to active trading, in analogy with equation (15) of the basic model. In (35), since As are more optimistic than Ps about the risky asset, either $\lambda > 1$ (if its denominator is positive) or $\lambda < 0$ (if its denominator is negative). If the risky asset is not too overpriced, it will earn a positive risk premium over the riskfree rate and will be perceived to do so by the Ps, implying $\lambda > 1$. It follows that $D < 0$, a negative return penalty to active trading. If the risky asset is so overpriced that its expected return is below the riskfree rate, and the Ps rationally perceive this to be the case, then $D > 0$.

3.2 Market Equilibrium

We normalize the per capita supply of the risky asset to be worth one unit of the numeraire. Then the per capita market clearing condition requires that

$$f w_A + (1-f) w_P = 1. \tag{38}$$

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 using (33), and solving for the price of the risky asset gives

$$p = \frac{f\overline{V}_A + (1-f)\overline{V}_P}{1 + R_F + \nu\sigma_S^2}. \tag{39}$$

By (39) and the definition of return,

$$\begin{aligned} \bar{R}_{SA} &= \overline{V}_A/p - 1 \\ &= \frac{(1-f)(\overline{V}_A - \overline{V}_P) + \overline{V}_A(\nu\sigma_S^2 + R_F)}{f\overline{V}_A + (1-f)\overline{V}_P} && (40) \\ &> R_F && (41) \end{aligned}$$

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

Similar steps yield

$$\bar{R}_{SP} = \frac{f(\overline{V}_P - \overline{V}_A) + \overline{V}_P(\nu\sigma_S^2 + R_F)}{f\overline{V}_A + (1-f)\overline{V}_P}. \tag{42}$$

Since the first term in the numerator is negative and the second is positive, depending upon parameter values $\bar{R}_{SP}$ can be greater or less than R_F.

Since the Ps are less optimistic, they view the risky asset as overpriced, so $w_P < w_A$. However, since the risky asset is in positive net supply, there is aggregate risk from holding it. So the Ps may still regard it as commanding a positive expected return premium as long as the As are not too optimistic, which would drive the price too high. Specifically, by (33) and (42), $w_P \overset{>}{<} 0$ are both possible.

3.3 Evolutionary Dynamics and the Stable Fraction of Active Investors

To derive the dynamics of the fraction of As, we now extend the equilibrium setting to allow for many ex ante identical stocks with independent normal returns. The analysis can be viewed as providing an equilibrium foundation for the partial equilibrium model of earlier sections, for the special case of the return assumptions in (15) where there is no factor risk ($\beta_A = \beta_P = 0$) and zero skewness ($\gamma_{1r} = \gamma_{1A} = \gamma_{1P} = 0$).

Models in evolutionary game theory often assume an infinitely large population of interacting agents, usually represented as a continuum. These models often assign revision protocols to agents describing how their behaviors change in response to their experiences. Based on these protocols such models typically derive deterministic evolutionary dynamics for the system, in the form of differential or difference equations for population shares (Sandholm 2010). Changes in the strategy shares in the population are viewed as averages over large numbers of individual strategy switches.

In this approach, randomness at the individual level is caused by the matching and the switching processes. In our model, there is an additional source of randomness: the payoffs of the strategies. In this section we assume that the risks of the stocks held by different individuals are diversifiable, so that the system still evolves deterministically.

Each individual holds only one stock, each of which is held by many investors. The optimization problem of any given A or P investor in any given stock is precisely identical to that in the single-security model analyzed earlier. The independence across stocks implies that the payoffs to A and P are independent across investors who trade in different stocks.

Each period, many pairs of individuals who have traded in different stocks are randomly selected for social interactions. With many stocks and many investors per stock, random fluctuations in returns and the randomness of the pairings (AP, PA, AA, PP) are diversified away, so by the law of large numbers the fraction converting to A evolves deterministically.

The interior stable fraction adopting A reflects a balance between two forces. On the one hand, owing to *SET*, A tends to spread. On the other hand, as overoptimism becomes more prevalent, risky securities become overpriced, and therefore tend to generate lower returns. Such returns do not attract emulation.

Specifically, there are $N = nm$ investors, m risky assets (stocks) with identical and independently distributed payoffs, and each stock has n investors, where we will take the limit as m but not n becomes large. During each period, each investor holds only one stock, along with the riskfree asset. The assumption that investors are imperfectly diversified is in the spirit of theories of limited investor information processing in which investors hold only subsets of available assets (Merton 1987); we take this to an extreme for simplicity.

In each period t, a fraction f_t of the investors in each stock are active, meaning that they hold overly optimistic belief $\overline{V}_A$ about the mean stock payoff. The P investors in each stock hold the correct belief $\overline{V}$. Assuming that the As are mistaken tilts the model against the spread of A, but we will see that A still survives. Each period investors are randomly assigned to stocks such that the fraction of A investors in each stock is equal. (We ignore discreteness issues in such assignments.)

Under these assumptions, we can analyze equilibrium trading in each stock independently based on that stock's investor base, so we omit notation to identify the specific stock. As before, risky assets start anew each period, so there is no repeated learning about the prospects of a given asset. In addition, investors do not draw inferences from price when forming demand for risky assets.

Let the degree of optimism of a type A investor for his chosen stock be denoted by $\kappa = \overline{V}_A/\overline{V} - 1 > 0$, where κ is constant over time. For simplicity of notation and without loss of generality, we set the riskfree rate $R_F = 0$. We also set the parameter a for the nonlinear term in the receiving function to zero (i.e., we eliminate the special salience of extreme news).[23]

Since stocks payoffs are independent and the investor bases of different stocks do not overlap, at each time t the analysis of market equilibrium is, stock by stock, identical

[23]The parameter a was only needed for the model's skewness predictions, but the return distributions in this section are Gaussian. Allowing for $a > 0$ makes expressions more cumbersome without additional insight. We have verified that Proposition 5 still holds when $a > 0$.

to that in Sections 3.1 and 3.2. By (39), active (overoptimistic) investors drive up the equilibrium price, p, of each stock so that p increases with the fraction f of A investors in the population:

$$p_t = \left(\frac{1 + f_t\kappa}{1 + \nu\sigma_S^2}\right)\overline{V} \tag{43}$$

This implies that the true equilibrium expected return $E[R_S]$ decreases with the fraction f of A investors:

$$E[R_S] = (\overline{V} - p)/p = \frac{\nu\sigma_S^2 - f_t\kappa}{1 + f_t\kappa}. \tag{44}$$

By (33), (40) and (42), the optimal holdings w_A and w_P also decrease with the fraction f of A investors in the population:

$$w_{At} = \frac{(1+\kappa)\nu\sigma_S^2 + (1 - f_t)\kappa}{(1 + f_t\kappa)\nu\sigma_S^2} \tag{45}$$

$$w_{Pt} = \frac{\nu\sigma_S^2 - f_t\kappa}{(1 + f_t\kappa)\nu\sigma_S^2}, \tag{46}$$

where the quantities above are the same for all stocks.

Each period, one investor from each stock is randomly selected, and these investors are randomly paired off (with one left over if m is odd), so the members of each pair are investors in different stocks. When m and therefore $N = mn$ is large, in each drawing the probability that a mixed pair is drawn (one A, one P) is arbitrarily close to $2f_t(1 - f_t)$. In the next period, anyone who is converted to A becomes optimistic about whatever stock he is assigned to, and anyone who is converted to P acquires objective beliefs about whatever stock he is assigned to.

So at date t, there are $m/2$ meetings of pairs of individuals. Let the meetings be indexed by j. In a given mixed meeting j, the returns experienced by the A and the P individuals are (suppressing t subscripts on return variables)

$$R_{Aj} = w_{At}R_{SAj}, \quad R_{Pj} = w_{Pt}R_{SPj}. \tag{47}$$

The sending and receiving functions are as in Section 2. So after $m/2$ meetings of pairs at date t, by (10) the change in the population frequency of A is

$$\begin{aligned} f_{t+1} - f_t &= \left(\frac{\chi_t}{2N}\right)\sum_{j=1}^{\frac{m}{2}} T_{AP}(R_{Aj}) - T_{PA}(R_{Pj}) \\ &= \left(\frac{\chi_t}{2N}\right)\sum_{j=1}^{\frac{m}{2}} B\left(R_{Aj}^2 - R_{Pj}^2\right) + C(R_{Aj} - R_{Pj}), \end{aligned}$$

where $B = b\beta$ and $C = b\gamma + c\beta$. Substituting equation (47) into the above gives

$$f_{t+1} - f_t = \left(\frac{\chi_t}{2}\right)\frac{1}{N}\sum_{j=1}^{\frac{m}{2}} B(w_{At}^2 R_{SAj}^2 - w_{Pt}^2 R_{SPj}^2) + C(w_{At}R_{SAj} - w_{Pt}R_{SPj}).$$

Letting m and hence the population size $N = nm$ approach infinity with n held fixed, we obtain a deterministic dynamic for the fraction of As. Since stock returns are i.i.d., applying the law of large numbers to the summation on the right hand side of the equation above, each term being averaged can be replaced with its expectation. Then the dynamic for the population frequency of A becomes

$$\frac{f_{t+1} - f_t}{f_t(1-f_t)} = \frac{1}{2n}(w_{At} - w_{Pt})\{B(w_{At} + w_{Pt})[(E_t[R_S])^2 + \sigma_S^2] + CE_t(R_S)\}, \quad (48)$$

where $E_t[R_S]$ is given in (46). By (45) and (46), $w_{At} - w_{Pt}$ and $w_{At} + w_{Pt}$ can be expressed as functions of f_t,

$$w_{At} - w_{Pt} = \frac{\kappa(1+\nu\sigma_S^2)}{(1+f_t\kappa)\nu\sigma_S^2} \quad (49)$$

$$w_{At} + w_{Pt} = \frac{(2+\kappa)\nu\sigma_S^2 + (1-2f_t)\kappa}{(1+f_t\kappa)\nu\sigma_S^2}. \quad (50)$$

By (48), the net conversion rate from P to A, $(f_{t+1} - f_t)/f_t$, is a decreasing function of f_t. Specifically, it is the product of $1 - f_t$ and the right hand side of (48), which is a decreasing function of f_t, since $w_{At} - w_{Pt}$, $w_{At} + w_{Pt}$ and $E_t(R_S)$ all decrease with f_t.

When f is small, the stocks have positive expected return premia, which means that strategy A earns high expected returns relative to P, i.e., $D < 0$.[24] In this circumstance, other investors tend to convert to A (becoming optimistic) as they hear about the high returns experienced using A. However, as the fraction of As becomes sufficiently large, the expected return premium on the risky asset declines or even turns negative, which limits the spread of A.

So long as the optimistic belief is not too extreme ($\kappa < \nu\sigma_S^2$) so that $E(R_S)$ is positive, the right hand side of (48) is also positive, regardless of f ($0 \le f \le 1$). Thus, owing to *SET*, the fraction of A increases indefinitely, and type A dominates the population.

However, if the As have sufficiently optimistic beliefs, then as f grows, the risky assets become highly overpriced, driving $E(R_S)$ negative. This results in an expected return penalty to A. As the actual and reported returns on A diminish, so does the net conversion

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

rate from P to A, which becomes negative when the fraction f of active investors becomes too large. So when the A belief is sufficiently optimistic, there exists a *stable fraction* $f^* \in (0,1)$ of type A such that if $f = f^*$, the net conversion rate from P to A is zero; if $f < f^*$, $\Delta f > 0$; and if $f > f^*$, $\Delta f < 0$.

By equation (48) and the fact that $w_{At} - w_{Pt}$ given in (49) is always positive, the stable fraction f^* satisfies $H(f^*) = 0$, where

$$H(f) \equiv B(w_{At} + w_{Pt})[(E_t[R_S])^2 + \sigma_S^2] + CE_t(R_S). \tag{51}$$

Substituting (44)-(46) into the above, $H(f^*) = 0$ can be equivalently written as $G(f^*) = 0$, where

$$G(f) \equiv B[(2+\kappa)\nu\sigma_S^2 + (1-2f)\kappa][(\nu\sigma_S^2 - f\kappa)^2 + \sigma_S^2(1+f\kappa)^2] + C\nu\sigma_S^2(1+f\kappa)^2(\nu\sigma_S^2 - f\kappa). \tag{52}$$

G is a cubic polynomial in f, with $G(0) > 0$. Assume $\nu\sigma_S^2 < 1$. Then when the As have sufficiently optimistic beliefs $\kappa > 2\nu\sigma_S^2/(1-\nu\sigma_S^2)$, $G(1) < 0$, and the discriminant of G is negative. It follows that there exists a unique $f^* \in (0,1)$ satisfying $G(f^*) = 0$.

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

Proposition 5 *If the type A investors are sufficiently optimistic ($\overline{V}_A > \overline{V}(2\nu\sigma_S^2)/(1-\nu\sigma_S^2)$), then there exists a stable fraction $f^* \in (0,1)$, such that $\Delta f > 0$ for $f < f^*$, and $\Delta f < 0$ for $f > f^*$. Corresponding to f^*, the expected return premium on the risky asset is negative.*

Since the stable fraction f^* of A satisfies $H(f^*) = 0$, we can use (51) to calculate how f^* varies with key model parameters. It is straightforward to verify that

$$\frac{\partial H}{\partial f} < 0,\ \frac{\partial H}{\partial \beta} > 0,\ \frac{\partial H}{\partial b} > 0,\ \frac{\partial H}{\partial c} < 0,\ \frac{\partial H}{\partial \gamma} < 0. \tag{53}$$

The first inequality in (53) derives from the fact that $E(R_S)$ decreases with the fraction of As. The greater the fraction of As, the more that stocks are overpriced, and the lower the expected return. To derive the second and the third inequalities, we substitute the equilibrium relation that holds at the stable fraction f^*,

$$b\beta(w_{At} + w_{Pt})[(E_t[R_S])^2 + \sigma_S^2] + (b\gamma + c\beta)E_t(R_S) = 0,$$

into the following partial derivatives:

$$\begin{aligned}
\frac{\partial H}{\partial \beta}\Big|_{f=f^*} &= b(w_{At}+w_{Pt})[(E_t[R_S])^2+\sigma_S^2]+cE_t(R_S) = -\frac{b\gamma E_t(R_S)}{\beta} \\
\frac{\partial H}{\partial b}\Big|_{f=f^*} &= \beta(w_{At}+w_{Pt})[(E_t[R_S])^2+\sigma_S^2]+\gamma E_t(R_S) = -\frac{c\beta E_t(R_S)}{b}.
\end{aligned}$$

The second and the third inequalities in (53) then result from the fact that the expected return on the risky asset is negative at the stable fraction of As. This fact also underlies the last two inequalities in (53), since

$$\begin{aligned}
\frac{\partial H}{\partial c} &= \beta E_t(R_S) \\
\frac{\partial H}{\partial \gamma} &= bE_t(R_S).
\end{aligned}$$

Applying the implicit function theorem to $H(f^*)=0$, where H is given by (50), using the inequalities in (53) gives

$$\frac{\partial f^*}{\partial \beta}>0,\ \frac{\partial f^*}{\partial b}>0,\ \frac{\partial f^*}{\partial c}<0,\ \frac{\partial f^*}{\partial \gamma}<0. \tag{54}$$

We therefore have:

Proposition 6 *If the type A investors are sufficiently optimistic ($\overline{V}_A > \overline{V}(2\nu\sigma_S^2)/(1-\nu\sigma_S^2)$), the stable fraction f^* of A increases with SET, β, and the tendency of receivers to extrapolate returns, b, decreases with conversability γ, and receiver susceptibility, c.*

The comparative statics in Proposition 6 for β and b are consistent with Proposition 2 Parts 4 and 5 respectively. The results for γ and c in Proposition 6 agree with Part 7 and Part 8 of Proposition 2 in the case of a positive penalty to active trading (i.e., $D>0$). According to Proposition 5, the equilibrium expected return of the risky asset is negative at the stable fraction f^* of A. This implies a positive penalty to active trading $D>0$ (see Section 3.1). Part 7 and Part 8 of Proposition 2 allow for the comparative statics for γ and c to go in either direction depending on which strategy has higher expected return. The equilibrium condition in this section pins these predictions down to the negative direction by showing that P has higher expected return.

Intuitively, greater susceptibility, c, helps transform the receiver only if the sender actually sends. In equilibrium A earns lower expected return than P (i.e., $D>0$); owing to *SET*, this reduces the sending probability by type A relative to P, which reduces the

probability that the receiver is converted. Thus, in the equilibrium setting, the stable fraction f^* of A decreases with c.

Furthermore, since A earns lower expected return than P, greater conversability γ works against the spread of A. In this case, greater conversability increases the reporting of returns that tend to be higher for P than for A. So in the equilibrium setting, the stable fraction f^* of A decreases with γ.

This is consistent with the conclusion of the partial equilibrium setting with $a = 0$ and $D > 0$. In the partial equilibrium setting, an opposing channel that helps A spread is the high salience of extreme returns, $a > 0$. As a result, higher conversability helps A exploit its extreme returns, causing it to spread more. However, in the equilibrium setting, we set $a = 0$, which eliminates this effect.

Also, as mentioned in Section 2.7.1, it is plausible that in most contexts conversability is greater for A than for P, $\gamma_A > \gamma_P$. In that case, intuitively we expect that an exogenous shift that promotes conversation, such as an increase in sociability, will tend to have a relatively strong effect on reporting of A, thereby promoting its spread.[25]

We do not wish to emphasize unduly the model implication that in equilibrium A has lower expected return than P (and associated comparative statics), because under a reasonable alternative assumption, this implication can be reversed. So far our model has assumed that the susceptibility of receivers, c, is the same regardless of whether the sender was an A or a P, so that the probability that a receiver is converted depends only on the sender's return. However, it is possible that a receiver who recognizes that A is riskier than P will be less willing to convert, for any given return, if the report came from an A. For example, a report of a 4% annual return might be much more attractive if it is about a riskfree asset than about a risky tech IPO. So we would expect receivers to be less susceptible to messages that come from an A. This would be reflected by having the receiver susceptibility parameter c in the receiving function be lower if the sender was an A than a P, $c_{SA} < c_{SP}$.

All the asset pricing equations in Sections 3.1 and 3.2 continue to hold when the receiver susceptibility parameter depends on the sender type. Under this assumption, upon deriving the dynamic for the population frequency of A, solving for the stable frequency f^*, and imposing reasonable parameter constraints, it is easy to show that when the difference in susceptibility is sufficiently large, the expected return premium on the risky assets at the stable fraction f^* is positive. Intuitively, a lower receiver susceptibility for messages from

[25]This point operates unambiguously in an extended model in which senders sometimes tell receivers about their strategy—its existence and logic—without mentioning performance.

A handicaps A in spreading through the population, which accommodates a positive risk premium. The detailed derivation is contained in Appendix C.

In particular, when $c_{SA} < c_{SP}$, the effect of SET, which favors spread of A, is opposed by the lower susceptibility of receivers to messages from As. If the handicap is large enough, the population dynamic has a stable frequency in which the net conversion from P to A becomes zero, even though the equilibrium expected return of the risky assets is positive. In such an equilibrium A earns a higher risk premium than P. This would affect the γ comparative statics since, as mentioned earlier, the intuition for the γ comparative statics depends on which strategy has higher expected return.

In summary, the comparative statics in the equilibrium setting for the stable fraction of As in the population are similar to those derived in the partial equilibrium setting Section 2.7.1 for the expected change in this fraction.

4 Concluding Remarks

We argue that success in the struggle for survival between investment strategies is determined by sending and receiving functions for the transmission of information about the strategies and their performance. In the model, owing to self-enhancing transmission, senders' propensity to communicate their returns is increasing in sender return. Furthermore, owing to naive extrapolation, the propensity of receivers to be converted is also increasing in sender return. Owing to the salience of extremes, the propensity of receivers to attend to and be converted by the sender is convex in sender return. More generally, we suggest that a fruitful direction for understanding how social interactions affect financial decisions is to study the factors that shape the sending and receiving functions, i.e., that cause an investor to talk about an investment idea, or to be receptive to such an idea upon hearing about it, as a function of the strategy return experienced by the sender.

Conversations are influenced by chance circumstances, subtle cues, and even trifling costs and benefits to the transactors. This suggests that small variations in social environment can have large effects on economic outcomes. For example, the model suggests that a shift in the social acceptability of talking about one's successes, or of discussing personal investments more generally, can have large effects on risk taking and active investing.

Much of the empirical literature on social interactions in investment focuses on *whether* information or behaviors are transmitted, and on what affects the strength of social contagion. Our approach suggests that it is also valuable to measure how *biases in the transmission process* affect the relative success of different kinds of behaviors.

More broadly, the approach offered here illustrates how cultural evolution can help explain stylized facts about investing and pricing. It would be interesting to extend the approach to study shifts in popularity of different money management vehicles, such as mutual funds, ETFs, and hedge funds.

Our approach also offers a microfoundation for research on fluctuations in investor sentiment toward different kinds of investment strategies. For example, observers have often argued that social interactions contribute to bubbles. Notably, the millennial high-tech stock market boom coincided with the rise of investment clubs and chat rooms. If the sending and the receiving functions of our model depend on the sender's return over multiple periods (rather than just the most recent period return), there can be overshooting and correction. Alternatively, if a higher frequency of active investors makes it more socially acceptable to discuss one's investment successes, the popularity of active strategies will be self-reinforcing. So our model, and more generally the social finance approach, offers a possible framework for modeling how the spread of investment ideas cause bubbles and crashes.

Appendices

A 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.

A.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 avoid the topic if it is bad. Suppressing i subscripts, let $\pi(R, x)$ be the utility to the sender of discussing his return R,

$$\pi(R, x) = R + \frac{x}{\beta'}, \tag{55}$$

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

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

$$\begin{aligned} s(R) &= Pr\left(x > -\beta' R | R\right) \\ &= 1 - F(-\beta' R), \end{aligned} \tag{56}$$

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

$$\begin{aligned} s(R) &= \frac{\tau_2 + \beta' R}{\tau_2 - \tau_1} \\ &= \frac{\tau_2}{\tau_2 - \tau_1} + \beta R, \end{aligned} \tag{57}$$

where $\beta \equiv \beta'/(\tau_2 - \tau_1)$, and where we restrict the domain of R to satisfy $-\tau_2/\beta' < R < \tau_1/\beta'$ to ensure that the sending probability lies between 0 and 1. This will hold almost surely if $|\tau_1|, |\tau_2|$ are sufficiently large. Equation (57) is identical to the sending function (4) in Subsection 2.2 with

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

In Sender's utility $\pi(R, x)$ of discussing return R, the parameter β' captures the value placed on mentioning one's high return experience, versus the appropriateness of doing so. The more tightly bound is Sender's self-esteem or reputation to return performance, the

larger is the parameter β', and hence the stronger is *SET*, as measured by β in the sending function (4) which is proportional to β'.

The constant γ in the sending function (4) reflects the *conversability* of the investment choice. When investment is a more attractive topic for conversation or when conversations are more extensive, as occurs when individuals are more sociable, higher γ shifts the distribution of x to the right (i.e., an increase in τ_2, for given $\tau_2 - \tau_1$, implies higher γ).

A.2 The Receiving Function

A convex increasing shape for the receiving function can derive from the combination of two effects: greater receiver attention to extreme return outcomes (inducing convexity), and, conditional upon paying attention, greater persuasiveness of higher return. Greater attention to extreme outcomes can be captured by having receiver attention be a positive quadratic function of the sender's return,

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

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

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

In other words, the receiver interprets sender return as providing information about the desirability of the sender's strategy. Regardless of whether such an inference is valid, it is tempting, as reflected in the need for the standard warning to investors that "past performance is no guarantee of future results." Overweighting of small samples (the law of small numbers) is a consequence of representativeness (Tversky and Kahneman 1974), the tendency to expect similarity between the characteristics of a sample and the underlying population.

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

With these assumptions on the A and B functions,

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

is a cubic function with positive coefficients. This implies positive coefficients on the quadratic Taylor approximation to $r(R)$, as in equation (5) in Section 2.

B Proof of Proposition 4

In Section 2.6, we denoted by R_A and R_P the returns of active and passive strategies over the period immediately prior to the conversation between A and P. We now consider an interval of calendar time of length Δ. We first examine how the unconditional population frequency of A changes over a given time period $[t, t+\Delta]$ after θN pairs of individuals meet, letting the size of population N approaches infinity. We then derive a stochastic differential equation which describes the continuous time dynamics for the evolution of the frequency of A in the population by letting the length of time period Δ shrink towards zero.

In the factor model for R_A and R_P as in (15), let μ and σ_r be the mean and standard deviation of the return of the common factor over a unit time interval, σ_A and σ_P the standard deviation over a unit time interval of the idiosyncratic return of the strategy A and P, and γ_{1A}, γ_{1P} denote the corresponding skewness. (Later we will specify a standard Gaussian diffusion process for the common factor return so that the factor skewness is zero.)

Suppose that over the interval $[t, t+\Delta]$, θN paired meetings occur in sequence. By (3), when population size N approaches infinity, the probability χ of drawing a mixed pair in any one of these meetings is $2f_t(1-f_t)$, up to to an error that is of the order $o(1/N)$. Letting ω be an index for the θN meetings, by (10), the change in the population frequency of A is up to an error that shrinks to zero with N

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

Substituting (15) into the above, we have

$$\begin{aligned} f_{t+\Delta} - f_t \;\approx\; & f_t(1-f_t)\frac{1}{N}\sum_{\omega=1}^{\theta N} a\beta[(\beta_A^3-\beta_P^3)r^3 + 3r^2(\beta_A^2\epsilon_{A\omega}-\beta_P^2\epsilon_{P\omega}) + 3r(\beta_A\epsilon_{A\omega}^2-\beta_P\epsilon_{P\omega}^2) + \epsilon_{A\omega}^3-\epsilon_{P\omega}^3] \\ & + B[(\beta_A^2-\beta_P^2)r^2 + 2r(\beta_A\epsilon_{A\omega}-\beta_P\epsilon_{P\omega}) + \epsilon_{A\omega}^2-\epsilon_{P\omega}^2] + C[(\beta_A-\beta_P)r + \epsilon_{A\omega}-\epsilon_{P\omega}] \\ & + D\Delta\{-(r\beta_A+\epsilon_{A\omega})[3a\beta(r\beta_A+\epsilon_{A\omega})+2B]-C\} + D^2\Delta^2[3a\beta(r\beta_A+\epsilon_{A\omega})+B] \\ & - aD^3\Delta^3\beta, \end{aligned} \tag{58}$$

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

When the population size N approaches infinity, by the law of large numbers the randomness coming from the matching process and from individual-specific return components average out. This allows replacing all terms involving ϵ in (58) with their expected values. Note that

$$\epsilon_i(t, t+\Delta) + \epsilon_i(t+\Delta, t+2\Delta) + \cdots + \epsilon_i(t+(m-1)\Delta, t+m\Delta) = \epsilon_i(t, t+1),$$

where $i = A, P$, and $m = 1/\Delta$. Taking the sum of the subinterval returns, squaring or cubing, taking the expectation, and recognizing (since the returns over time are i.i.d.) that all the cross-time terms are zero, we find that the moments of the return distributions are proportional to the length of the return interval $[t, t+\Delta]$,

$$\begin{aligned} E[\epsilon_i(t, t+\Delta)^2] &= E[\epsilon_i(t, t+1)^2]\Delta = \sigma_i^2\Delta \\ E[\epsilon_i(t, t+\Delta)^3] &= E[\epsilon_i(t, t+1)^3]\Delta = \sigma_i^3\gamma_{1i}\Delta. \end{aligned} \tag{59}$$

By (58) and (59), and taking the limit as N approaches infinity,

$$\begin{aligned} f_{t+\Delta} - f_t \;=\; & \theta f_t(1-f_t)\{a\beta[(\beta_A^3-\beta_P^3)r^3 + 3r(\beta_A\sigma_A^2-\beta_P\sigma_P^2)\Delta + (\gamma_{1A}\sigma_A^3-\gamma_{1P}\sigma_P^3)\Delta] \\ & + B[(\beta_A^2-\beta_P^2)r^2 + (\sigma_A^2-\sigma_P^2)\Delta] + C(\beta_A-\beta_P)r - aD^3\Delta^3\beta \\ & -D\Delta[3a\beta\beta_A^2r^2 + 3a\beta\sigma_A^2\Delta + 2B\beta_A r + C] + D^2\Delta^2(3a\beta r\beta_A + B)\}. \end{aligned} \tag{60}$$

Next, we shrink the length of each period Δ towards zero and derive the continuous-time evolutionary dynamic of the population frequency of type A as a stochastic differential equation. We assume that the cumulative return R_t (log price change) of the common factor between time 0 and t follows a Gaussian random walk (with a zero drift in order to be consistent with the assumption in Section 2.6 that the expected return of the common factor is zero):

$$dR_t = \sigma_r dW_t,$$

where W is a standard Brownian motion. As $\Delta \to 0$, $r = r(t, t+\Delta)$ can be replaced by dR. By the properties of product of stochastic differentials, r^2 can be replaced by $(dR)^2 = \sigma_r^2 dt$, and r^3 can be replaced by $(dR)^3 = 0$. Thus, in an infinite population and letting $\Delta \to 0$, a stochastic differential equation for the fraction of type A follows from (60):

$$df_t = \theta f_t(1 - f_t)[Kdt + C(\beta_A - \beta_P)\sigma_r dW_t], \tag{61}$$

where K is a constant that depends on the model parameters that characterize the sending and receiving functions, as well as the return distributions of the strategies,

$$K = a\beta(\gamma_{1A}\sigma_A^3 - \gamma_{1P}\sigma_P^3) + B[(\beta_A^2 - \beta_P^2)\sigma_r^2 + (\sigma_A^2 - \sigma_P^2)] - CD. \tag{62}$$

To prove the comparative statics in Proposition 4, we show the following stochastic dominance property for the evolution of the fraction of A in the population.

Lemma 1 *Consider two sets of model parameters Θ and Θ' (each being a vector (a, b, c, β, γ, σ_r, β_A, β_P, σ_A, σ_P, γ_{1r}, γ_{1A}, γ_{1P})) such that the corresponding values for $C(\beta_A - \beta_P)\sigma_r$ are the same but $K' > K$. Then for any given time $t > 0$ and along any given path of realizations for the Brownian motion term dW, the fraction of A in the population satisfy $f'_t \geq f_t$.*

Corresponding to the set of model parameters Θ', the fraction of type A in the population f' follows a diffusion process that is similar to the dynamics (61) for f:

$$df'_t = \theta f'_t(1 - f'_t)[K'dt + C(\beta_A - \beta_P)\sigma_r dW_t]. \tag{63}$$

By assumption, the two sets of parameters lead to the same value $C(\beta_A - \beta_P)\sigma_r$ in the diffusion coefficient, but $K' > K$ in the drift term. Hence, $f' - f$ satisfy the following diffusion process:

$$d(f'_t - f_t) = \theta[K' f'_t(1 - f'_t) - K f_t(1 - f_t)]dt + \theta C(\beta_A - \beta_P)\sigma_r[f'_t(1 - f'_t) - f_t(1 - f_t)]dW_t. \tag{64}$$

At date 0, f' and f start at the same initial value and have the same diffusion coefficients, but the drift term of f' is larger than that of f. Hence, $f' - f$ is locally deterministic with positive drift near $t = 0$. This implies that $f'_t > f_t$ when $t > 0$ is sufficiently small.

We next prove by contradiction that for any $t > 0$, $f'_t \geq f_t$ along any identical path of realizations for the Brownian motion innovations. If at some time T, $f'_T < f_T$, then there must exist a time $0 < \tau < T$ such that $f'_\tau = f_\tau$, because $f' - f$ has a continuous sample

path and takes positive value when $t > 0$ is small. However, at time τ, the instantaneous diffusion coefficient of $f' - f$ is zero (because $f'_\tau = f_\tau$), but the drift term is positive (because $f'_\tau = f_\tau$ and $K' > K$). Thus, the process $f' - f$ has a reflecting barrier at zero: if it takes on the value of zero it will subsequently have positive values with probability one. This contradicts $f'_T < f_T$ for $T > \tau$. So it follows that $f' \geq f$ along any given path of realizations for the Brownian motion term, and the set of τ such that $f'_\tau = f_\tau$ has zero density since $f' - f$ has a reflecting boundary at zero.

It is straightforward to prove the comparative statics in Proposition 4 based on the path-by-path stochastic dominance result above, and the following observations:

1. A change in the value of any of the parameters D, γ_{1A}, σ_A, a does not affect $C(\beta_A - \beta_P)\sigma_r$ (the same is true for β when $c = 0$). Thus, Lemma 1 applies;
2. $\frac{\partial K}{\partial D} = -C < 0$;
3. $\frac{\partial K}{\partial \gamma_{1A}} = a\beta > 0$;
4. $\frac{\partial K}{\partial \sigma_A} = 3a\beta\gamma_{1A}\sigma_A^2 + 2B\sigma_A > 0$;
5. $\frac{\partial K}{\partial a} = \beta(\gamma_{1A}\sigma_A^3 - \gamma_{1P}\sigma_P^3) > 0$;
6. $\frac{\partial K}{\partial \beta} = a(\gamma_{1A}\sigma_A^3 - \gamma_{1P}\sigma_P^3) + b[(\beta_A^2 - \beta_P^2)\sigma_r^2 + (\sigma_A^2 - \sigma_P^2)] > 0$.

C Equilibrium When Receiver Susceptibility Depends on Sender Type

In the main text, our model assumes the receiver susceptibility parameter c in the receiving function is the same regardless whether the sender is an A than a P. Here we study the equilibrium expected return in the setting of Section 3 when the receiver susceptibility satisifies $c_{SA} < c_{SP}$ (i.e., after hearing a given return, receivers are less likely to switch strategy if it comes from an active type).

All the asset pricing equations in Sections 3.1 and 3.2 continue to hold when the receiver susceptibility parameter depends on the sender type. The same steps in Section 3.3 can be applied to derive the dynamic of the fraction of As. When $c_{SA} < c_{SP}$, the dynamic for the population frequency f_t of A becomes

$$\begin{aligned} \frac{2n(f_{t+1} - f_t)}{f_t(1 - f_t)} &= B(w_{At}^2 - w_{Pt}^2)[E_t(R_S)^2 + \sigma_S^2] + b\gamma E_t(R_S) \\ &+ \beta(c_{SA}w_{At} - c_{SP}w_{Pt})E_t(R_S) + (c_{SA} - c_{SP})\gamma. \end{aligned} \tag{65}$$

The stable frequency f^* now satisfies $\hat{H}(f^*) = 0$, where

$$\hat{H}(f) \equiv B(w_{At}^2 - w_{Pt}^2)[E_t(R_S)^2 + \sigma_S^2] + b\gamma E_t(R_S) + \beta(c_{SA}w_{At} - c_{SP}w_{Pt})E_t(R_S) + (c_{SA} - c_{SP})\gamma. \tag{66}$$

If the difference in susceptibility is sufficiently large,

$$c_{SP} - c_{SA} > \frac{B\kappa[(2+\kappa)\nu\sigma_S^2 + \kappa](1+\nu\sigma_S^2)}{\gamma\nu^2\sigma_S^2}, \tag{67}$$

then the RHS of (65) is negative, and hence the net conversion from P to A is negative, when evaluated at the fraction of A corresponding to $E(R_S) = 0$. Since both the net conversion rate from P to A and $E(R_S)$ decrease with f, it follows when the difference in susceptibility is sufficiently large, the expected return premium on the risky asset at the stable fraction f^* is positive.

D Trading Volume

We now generalize the equilibrium model to provide implications for volume of trade, by allowing differences in optimism about the risky asset among A investors. One interpretation of A versus P considered previously is that the As are unduly optimistic about a given risky security, whereas the Ps are not. An alternative interpretation, which we focus on here, is that A has a broader belief that stock picking or market timing is a worthwhile activity. Investors who believe that these are worthwhile will investigate to refine their valuations of the risky asset. In contrast, passive investors by assumption share some common prior belief (some conventional view prevalent in society), do not investigate further, and hence remain in agreement. In consequence, actives form divergent beliefs about the asset whereas passive investors do not.

We therefore assign heterogeneous expectations about the value of the risky asset to the As,

$$\overline{V}^{Ak} = \overline{V}^{A} + \psi^k, \tag{68}$$

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

Owing to the diversity of expectations among the As, they trade with each other, which contributes to higher volume of trade as a function of the frequency of A in the population. However, owing to the difference in belief between As and Ps, there is also trading between individuals of different types.

In general, the diversity of the As makes the analysis of evolution of the population more complex. To simplify, we let u be sufficiently close to zero that the evolution of the population is arbitrarily well approximated by a setting in which the As are identical.

We additionally let the difference in beliefs of the As and Ps become arbitrarily close to zero more rapidly than u does, i.e., $(\overline{V}_A - \overline{V}_P)/u \to 0$. This captures in extreme form the idea that the dispersion in beliefs among the actives is wider than the difference between the average beliefs of the As and the Ps. Under this assumption, volume is dominated by trading amongst A's rather than between types. As a result, as the frequencies of the different types shift, the qualitative prediction that volume of trade increases with the fraction of As remains valid.

Proposition 7 *Under the assumptions of this subsection, a higher fraction of As in the population implies higher volume of trade.*

Proposition 2 gives predictions about the conditions under which the expected fraction of As grows. Proposition 7 suggests that in a generalization in which As have diverse opinions, under appropriate conditions the comparative statics of Proposition 2 provide corresponding predictions about the determinants of increased trading volume.

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

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