The Social Dynamics of Performance*

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September 13, 2012

Abstract

A common empirical finding is that mutual fund managers do not maintain their performance. I show that social interactions can explain this fact. To do so, I introduce word-of-mouth communication within a rational-expectations equilibrium model. In my model, a “crowd” of managers meet at random times and exchange ideas. This novel form of learning simultaneously allows prices to become more efficient and managers to reap larger profits, and yet causes managers’ alpha to become insignificant. The main implication is that increased efficiency does not prevent managers from extracting large dollar rents. Increased efficiency, however, does prevent alpha from capturing managers’ rents. By increasing price informativeness, social interactions further produce momentum in stock returns and induce most managers to become momentum traders, consistent with empirical findings. Overall, my results indicate that word-of-mouth communication plays an important role in the mutual fund industry.

Keywords. rational-expectations equilibrium, mutual funds, performance persistence, performance measure, momentum, word-of-mouth, information percolation.

JEL Classification. D53, D82, D83, D85, G14, G23.

*I am particularly indebted to my advisors Bernard Dumas and Julien Hugonnier for their support and the many insights they provided. I also wish to thank Daniel Andrei, Harjoat S. Bhamra, Jérôme Detemple (Gerzensee discussant), Pierre Collin-Dufresne, Michal Dzieliński, Ruediger Fahlenbrach, Damir Filipovic, Amélie Gros, Michael Hasler, Jan Peter Kulak, Matthias Kurmann, Semyon Malamud, Loriano Mancini, Erwan Morelec, Rémy Praz, Christopher Robotham, Cornelius Schmidt, Norman Schuerhoff, Anders Trolle, and seminar participants at the Gerzensee Doctoral Workshop and the EPFL research seminar for their invaluable advice. Financial support from the Swiss Finance Institute and from NCCR FINRISK of the Swiss National Science Foundation is gratefully acknowledged.

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1 Introduction

There is ample evidence that the performance of mutual fund managers does not persist.\footnote{Barras, Scaillet, and Wermers (2010) find that the fraction of skilled managers has dropped from 14% in the early 90s to a mere 2% in the last decade. Jensen (1968), Malkiel (1995), Gruber (1996) and Carhart (1997) find that most mutual funds fail to outperform, and often underperform, passive benchmarks, even before transactions costs. See Wermers (2000) for a literature review.} The vast majority of managers are unable to generate abnormal returns and a significant fraction even underperforms passive benchmarks. Moreover, managers who outperform, a handful of top performers, seldom maintain their performance.

That performance does not persist is usually taken to imply that managers do not possess superior information (e.g., Carhart (1997)). In this paper I show that a manager, who possesses superior information, does not necessarily maintain her performance if she interacts socially with other managers. To do so, I develop a rational-expectations equilibrium à la Grossman and Stiglitz (1980) and Wang (1993), in which agents gather information through word-of-mouth communication. In the “noisy-rational expectations” literature, the typical setting involves a population of agents endowed with private information, who attempt to infer the information of other agents from prices. Other learning channels are virtually absent. In my model, social interactions account for an alternative channel whereby information is passed from one agent to another through private conversations, naturally complementing the price-learning channel. Social interactions simultaneously allow prices to become more efficient and better-informed managers to reap larger profits, and yet cause their performance, as traditionally measured (e.g., alpha of Jensen (1968)), not to persist. This result indicates that increased efficiency does not prevent managers from extracting large rents. Increased efficiency, however, does prevent traditional measures of performance from capturing managers’ rents.

My model builds on a large literature arguing that social interactions play an essential role in the marketplace.\footnote{See Hong, Kubik, and Stein (2005) and Cohen, Frazzini, and Malloy (2008) for references related to the mutual fund industry. Massa and Simonov (2011) show that college-based interactions influence portfolio decisions. Hong, Kubik, and Stein (2004) show that investors find the market more attractive when more of her peers participate. Brown, Ivkovic, Smith, and Weisbenner (2008) reach similar conclusions. Other evidence includes Grinblatt and Keloharju (2001) or Ivkovic and Weisbenner (2005).} For instance, a survey by Shiller and Pound (1989) shows that interpersonal communications are an important component of institutional investors’ decisions. To the question “Was the fact that someone (whom you know or may know of) bought stock in the company influential in getting you to buy the stock ?”, 44% answered “yes”. While the empirical prevalence of word-of-mouth communication is increasingly acknowledged, theory has made little headway in this direction.

Introducing social interactions within a rational-expectations equilibrium represents
my main contribution. I capture word-of-mouth communication with a single parameter—the intensity of social interactions. It is the only parameter that causes my model to differ from a traditional rational-expectations equilibrium model. I consider a “crowd” of fund managers that attempt to forecast some fundamental to be revealed in, say, one year from now. Managers initially develop a working idea regarding the fundamental. To prevent prices from fully revealing the fundamental, I insert noise traders whose orders continuously blur the price signal. Now, if one allows the social intensity parameter to be positive, the central contribution of my model appears—managers may socially refine the idea they initially developed on their own. They meet at random times and share their ideas until the fundamental is revealed. When two managers meet, information flows in both directions as managers bounce ideas off of one another. After the meeting, managers wind up with new pieces of information and trade. By clearing the market, the price centralizes conversation outcomes, albeit imperfectly due to noise trading.

This process leads to a novel form of learning, which includes a common and a private channel. What makes learning unique in my model is the way the private channel fits into the learning process and how the private channel affects the common channel. The pattern of information arrival is as follows. When managers are socially inactive, they analyze the price—the common channel—in an effort to infer private conversations among other managers. Information aggregated through the price flows tick-by-tick, which induces smooth and frequent updates in managers’ views. For most managers, conversations—the private channel—take place every once in a while. But upon meeting someone, managers obtain large pieces of information and significantly update their expectations. Private conversations ultimately feed back into the price through the trading process and make the public channel increasingly effective. If social interactions are sufficiently intense, the market learning process improves at great speed; a manager becomes progressively unable to preserve her informational advantage before the market catches up with her—her performance does not persist.

Consistent with empirical findings, most managers in my model cannot elude this mechanism, except a small group of top performers. This result is perhaps surprising considering the rich information heterogeneity triggered by social interactions. While managers hold one idea initially, some may entertain many meetings but others may be less successful. Therefore, only a subset of managers eventually get a “good” idea—many pieces of information—about the fundamental. Building on Stein (2008), good ideas do not travel all over the marketplace but remain localized. In my model, managers with good ideas do not talk with those who hold fewer ideas. This clustering of information

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allows managers to longer preserve their informational advantage. And yet, even if a manager gets a good idea, market efficiency eventually offsets her informational advantage. This mechanism may be powerful enough to make it literally impossible to distinguish alphas generated by managers with respectively good and few ideas. Only exceptionally good ideas allow a manager to sustain a significant alpha.

Nevertheless, this result does not imply that managers do not perform. Managers’ performance only becomes apparent when measured in dollar value. Before accelerating the information flow through prices, private conversations first allow managers to improve their market-timing ability. Managers with good ideas are better able to speculate and rapidly accumulate large profits in dollar value. Hence, even if price informativeness eventually weakens their timing ability, these managers pocket substantial profits in the meantime. In contrast, lesser-informed managers immediately rally to the market consensus and lose their timing ability. Information heterogeneity therefore creates large and persistent spreads in trading gains across managers.

The last point suggests that, as word-of-mouth communication intensifies, alpha fails to capture two aspects of managers’ performance. First, managers’ alpha rapidly becomes insignificant while managers may still be adding significant dollar value. As a result, alpha underestimates performance persistence. Second, alpha quickly becomes unable to tell managers apart, despite large spreads in dollar value. Overall, the dollar value a manager adds is a better measure of her performance. This prediction is line with recent evidence in Berk and van Binsbergen (2012).

The model offers two additional implications. First, social interactions produce momentum in stock returns, one of the most pervasive facts in Financial Economics.\(^4\) That my model generates momentum is intriguing for two reasons. Firstly, in a rational-expectations equilibrium, returns usually exhibit reversal. Secondly, in my model, momentum is a rational phenomenon, which is not simply driven by a risk factor (noise trading). Momentum hinges upon the diffusion of information through private conversations.\(^5\) Carhart (1997) argues that the weak evidence of performance persistence in the mutual fund industry is the sole result of the one-year momentum effect. By providing a new theory for momentum based on social interactions, my model suggests that profits made on momentum are rather modest and that managers pursuing momentum strategies do not maintain their performance.

\(^4\)See Poterba and Summers (1988), Jegadeesh and Titman (1993), Rouwenhorst (1998), Menzly and Ozbas (2010) and Moskowitz, Ooi, and Pedersen (2011), among others. This result is consistent with Wermers (1999) who argues that mutual fund managers are likely to play an important role in the momentum mechanism.

Second, social interactions give rise to trading patterns that are consistent with those identified in the mutual fund industry. By increasing price informativeness, social interactions encourage lesser-informed managers to chase the trend in an attempt to “free-ride” on the information of others. Instead, managers with superior information tend to break away from the herd to exploit their informational advantage, as in Coval and Moskowitz (2001). As social interactions intensify, the market digests more and more information, inducing even well-informed managers to eventually align with the market consensus. For most managers, momentum trading becomes sooner or later an optimal strategy. This result is in line with Grinblatt, Titman, and Wermers (1995) who find that 77% of mutual funds in their sample are momentum investors.

After discussing related works, the balance of the paper is as follows. Sections 2 and 3 respectively present and solve the model. Sections 4, 5 and 6 contain the results. Section 7 concludes. Mathematical derivations are collected in the technical appendix.

Review of the Literature

In the absence of social interactions, my model nests the setup of He and Wang (1995), except for allowing trading to be continuous. This setup serves as a natural benchmark against which to evaluate the effects of social interactions. Private information is dispersed among investors and learning is exclusively guided by prices. This framework has two additional advantages: first, it involves an economy with a finite horizon and therefore allows time to play a role, an important requirement for studying performance persistence. Second, this framework involves long-lived information, a necessary feature for social interactions to impact prices. My paper differs from He and Wang (1995) in two respects, though. While He and Wang (1995) investigate the effect of dispersed information on trading volume, my main focus is on performance. But more important, unlike He and Wang (1995), my purpose is to let agents interact socially. I show that social interactions endogenously modify the information structure.

I model social interactions based on the recent developments in the “information-percolation” literature initiated by Duffie and Manso (2007). Information typically diffuses among a population of agents through random meetings. This literature mostly applies the “percolation” of information to decentralized markets—agents meet to trade. Now, if markets are centralized but information is not (it is dispersed), Andrei and Cujean (2011) show that information percolation fulfills another task—agents meet to share their information. This approach to modeling social interactions, which I follow in this paper, is also advocated by Andrei (2012). Yet, unlike Andrei and Cujean (2011) and Andrei (2012), agents are free to trade whenever they receive new information.

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6See also Brennan and Cao (1997) and Feng and Seasholes (2004).
changes the pattern of information arrival and reconciles the trading and the meeting frequency. Furthermore, unlike Andrei (2012), information is inherently long-lived in my model, thus allowing me to study how long informational advantages subsist. Finally, by adapting the percolation mechanism to embed the result of Stein (2008)—good ideas stay local—I can illustrate the relentless effect of social interactions on market efficiency.

A well-accepted explanation for the lack of performance persistence in the mutual fund industry is that of Berk and Green (2004). If the provision of funds by investors is competitive and superior managerial ability is scarce, abnormal performance attracts flows of funds that compete away outperformance next period. As a result, economic rents flow to managers who create them, not to investors who invest in them. The view expressed in this paper is distinct from theirs in several respects. First, the mechanism I highlight does not rely on fund flows. Performance becomes non-persistent even though managers ignore flows into and out of the fund. Second, while Berk and Green (2004) build their explanation on the notion of “superior ability”, the source of which they do not model, mine is based on the familiar notion of information heterogeneity. Some managers are endogenously better-informed than others. Finally, the model of Berk and Green (2004) is partial equilibrium; trading does not affect benchmark returns. My results rely on an equilibrium mechanism whereby prices become more efficient.

2 A Model of Socially-Interacting Fund Managers

The goal of this section is to introduce social interactions in an otherwise standard Grossman and Stiglitz (1980) framework. Subsections 2.1 and 2.2 first present the setup of the economy along with its information structure. Subsection 2.3 then describes how fund managers interact socially in my model.

2.1 Assets, Trading and the Economy

Both phenomena I study—non-persistent performance and short-lived market-timing ability—call for a setup in which time is allowed to play a role. I therefore consider an economy with a finite horizon $T < \infty$. The economy features two assets. The first asset is a risky stock with equilibrium price $P_t$ at time $t$. The stock pays a liquidating dividend $\Pi + \delta$ to be revealed at the announcement date $T$ and which I regard as the stock’s fundamental value. The second asset is a riskless claim whose supply is perfectly elastic. Its rate of return is normalized to $r = 0$, as in He and Wang (1995).\footnote{See Chevalier and Ellison (1999a), Coval and Moskowitz (2001), Cohen, Frazzini, and Malloy (2008) and Christoffersen and Sarkissian (2009).}

\footnote{In the noisy rational-expectations literature, the riskfree rate is widely assumed to be exogenous. See, for instance, Admati (1985), Wang (1993), He and Wang (1995) or Brennan and Cao (1996).}
My purpose is to introduce social interactions whereby agents meet and share information on the time span \([0, T]\). It is thus important to let agents trade when they receive new information. Therefore, both assets are continuously available for trading.

The economy is populated with a crowd (a continuum) of fund managers. Each manager \(j\) in the crowd attempts to predict the fundamental value of the stock. Manager \(j\) does so by analyzing the tape and by privately discussing with other managers. Information collected by manager \(j\) up to time \(t\) is contained in her information set \(\mathcal{F}_t^j\).

I am interested in the heterogeneity of information \(\mathcal{F}_t^j\) triggered by social interactions among fund managers (managers have information motives to trade). Differences in risk aversion is not my main focus. I thus assume that managers share a common absolute risk aversion \(\gamma\) and, for simplicity, exhibit CARA utility.

To prevent prices from fully revealing the fundamental, I introduce noise traders—agents who trade for reasons unrelated to fundamental information.\(^9\) They have an inelastic demand of \(1 - \Theta\) units of the stock (in total supply of 1). The remainder \(\Theta\) represents the supply of the stock (available to managers). The supply evolves according to an Ornstein-Uhlenbeck process that mean-reverts to zero:

\[
d\Theta_t = -a_{\Theta} \Theta_t dt + \sigma_{\Theta} dB^\Theta_t. \tag{1}
\]

Noise trading makes the supply in (1) noisy through the Brownian shock \((B^\Theta_t)_{t \geq 0}\). This shock has an amplitude of \(\sigma_{\Theta} > 0\) and is reversed at speed \(a_{\Theta} > 0\).

A manager’s problem often has two layers, one pertaining to the optimal contract that originates from the portfolio delegation of individual investors. The other relates to a manager’s optimal asset allocation. Since my purpose is to study managers’ performance only, I abstract from the former.\(^10\) The problem of a manager \(j\) is to find an optimal portfolio strategy \(\theta_t^j\) maximizing her expected utility over terminal wealth

\[
E \left[ -e^{-\gamma W_T^j} \mid \mathcal{F}_T^j \right] \tag{2}
\]

subject to the constraint

\[
W_T^j = W_0^j + \int_{[0, T]} \theta_{t-}^j dP_t + \theta_T^j - \Delta P_T. \tag{3}
\]

Trading in (3) allows for a jump in prices of size \(\Delta P_T\) at the announcement date, an

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\(^11\) Her portfolio \((\theta_t^j)_{t \geq 0}\) is assumed to be a predictable process.
intuition for which follows shortly.

I make two modeling choices regarding (3). First, I neglect fund flows. One may think of funds in my model as closed-end funds.\footnote{See Chevalier and Ellison (1997) and Sirri and Tufano (1998) for empirical treatments.} Second, as in Koijen (2012), I do not impose short-sales or borrowing constraints, although managers may face certain trading restrictions.\footnote{See, for instance, Almazan, Brown, Carlson, and Chapman (2004).} Relaxing this assumption would unnecessarily obscure the results.

\section{2.2 The Information Structure}

The fundamental value of the stock has two parts, $\Pi$ and $\delta$. Managers do not observe $\delta$, nor do they get information about it. They view $\delta \sim \mathcal{N}(0, \sigma_\delta^2)$ as an independently-drawn normal variable. Because managers cannot possibly learn about it, $\delta$ represents some kind of \textit{residual uncertainty}.\footnote{See Grundy and McNichols (1989), Hirshleifer, Subrahmanyam, and Titman (1994), He and Wang (1995) or Manela (2011) for other references making use of residual uncertainty.} Residual uncertainty implies that the final payoff is not completely transparent to managers. I need this feature to keep managers with highly accurate information from posting massive orders at the announcement date and thus to ensure that the model is well specified. One can regard residual uncertainty as capturing a failure of information to completely flow through prices (e.g., the post-earning announcement drift of Bernard and Thomas (1989)).\footnote{Alternatively, $\delta$ may account for a shortfall in forecasting a firm’s default. The price of bonds or equities often drops precipitously at or around the time of default, as in Duffie and Lando (2001).} Since residual uncertainty remains unanticipated by the market, it accounts for a surprise at the announcement date; this explains the possibility of a price jump $\Delta P_T$ in (3).

Managers only get information about $\Pi$, the other part of the stock’s fundamental value. This information is organized as follows. Consider the crowd $(I, \mathcal{I}, i)$ of managers and split it into two groups $I = I_1 \cup I_2$. Managers in the first group $I_1$ observe $\Pi$. They constitute an initial fraction $1 - \omega_0$, which will move endogenously through social interactions.\footnote{$(I, \mathcal{I}, i)$ is a nonatomic space with $i(I) = 1$, i.e. its size is 1. See Duffie (2011) for further details.} These managers are \textit{informed} and are therefore labelled by $i$ (that is, $j = i$). Managers in the second group $I_2$, who represent the remaining fraction $\omega_0$, do not observe $\Pi$. They need to learn about it. As \textit{learning} individuals, they are indexed by $l$ (that is, $j = l$). Each manager $l$ is endowed with an initial signal about $\Pi$:

$$S^l = \Pi + \epsilon^l,$$

which I view as a \textit{working idea} that managers $l$ have privately developed. Working ideas are imperfect, as they contain an agent-specific error $\epsilon^l \sim \mathcal{N}(0, \sigma_S^2)$.\footnote{Errors are initially independent among the crowd; $\epsilon^k \perp \epsilon^l$, $\forall k \neq j \forall j \in I_2$ and $\epsilon^l \perp (B^\Theta_{t})_{t \geq 0}$.} Managers $l$
assume that $\Pi$ and the initial supply $\Theta_0$ are independent and start with prior beliefs $\Pi \sim \mathcal{N}(0, \sigma^2_{\Pi})$ and $\Theta_0 \sim \mathcal{N}(0, \frac{\sigma^2_{\Theta}}{2\alpha})$.\(^{18}\)

Now comes the central feature of my model. From $t = 0$ onward, managers $l$ interact through private meetings and \textit{socially refine the idea in (4) they initially developed on their own}. In particular, a manager $l$ builds a collection $\{S^l_k\}_{k=1}^{n^l}$ of ideas, where the number $n^l$ of ideas she collected evolves through the vagaries of her meetings. This meeting process, a central component of my model, is described in the next subsection.

### 2.3 Modeling the Social Network of Fund Managers

Mutual fund managers interact socially in several ways. Evidence indicates that managers keep in touch with company’s chairmen who were former classmates (Cohen, Frazzini, and Malloy (2008)) or entertain conversations with other managers who operate in the same city (Hong, Kubik, and Stein (2005)). But all kinds of social interactions do not result in the same information quality. For instance, ideas exchanged on large-access investment forums, such as Yahoo groups or Motley Fool, have presumably less content than those exchanged on a highly-selective online community of top investors, such as The Value Investor Club or The Alburn Village. And information collected through direct interactions with firm insiders or through controversial expert networks is likely to be highly accurate. During the trial of one such expert network, a former hedge-fund executive testified that the information provided was “absolutely perfect”.\(^{19}\)

I want the social dynamics of my model to reproduce this kind of information heterogeneity. While “cheap talk” regularly takes place through phone calls, dinners or cocktail parties, genuinely “good” ideas remain localized and do not travel all over the marketplace. Building on Stein (2008), good ideas stay confined to a small group of managers. Finally, “perfect” information is costly and therefore does not circulate. Such costs are absent of my model but can be thought of as the time it takes to acquire insider information. This clustering of information allows managers to longer keep their informational advantage and allows me to highlight the impact of social interactions on price informativeness—even if a manager develops good ideas, it is almost impossible for her to preserve her informational advantage before the market catches up with her.

To formalize this idea, I adapt the information-percolation setup developed in Duffie, Malamud, and Manso (2009). This approach to modeling word-of-mouth communication contrasts with alternative formulations in the literature. Some researchers use graph

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\(^{18}\)As in He and Wang (1995), the prior variance of the noisy supply is set to its stationary level.

theory to model the information structure—agents are “nodes” of a network. The resulting network is often admittedly complex and the results are sensitive to its specification (see Ozsoylev and Walden (2011)).\textsuperscript{20} Another strand of the literature resorts to epidemiological models—agents typically progress from “susceptible” to “infected” and back to “recovered”. Because learning is tantamount to the spread of a disease, this approach does not accommodate Bayesian updating nor learning from prices. Additionally, generating a wide heterogeneity among agents is challenging.\textsuperscript{21}

Information percolation, the mechanism through which I model social interactions, circumvents these issues. It is tractable. It leads to strong information heterogeneity. It allows for Bayesian learning and accommodates learning from prices. In Andrei and Cujean (2011), we show that such advantages make information percolation a particularly suited device to model word-of-mouth communication in centralized markets. Yet, information percolation in its usual form does not allow “good” ideas—many ideas—to stay local. Good ideas travel over the whole population of agents. Also, while a potentially vast number of ideas, an interpretation of which is delicate in the present context, may be exchanged, literally “perfect” information is only accessible to a negligible fraction of the population. These are two aspects I now wish to address.

Each manager \( l \) is attributed a Poisson counter \((N^l_t)_{t \geq 0}\), which counts the number of meetings manager \( l \) has had up to time \( t \). The probability that a manager \( l \) meets someone in a small time interval, \( dt \), is \( \eta dt \). The parameter \( \eta \) captures the intensity of social interactions. It is the only parameter that causes my model to differ from a traditional rational-expectations equilibrium model. If two managers, \( k \) and \( j \), ever meet, they are randomly selected from the crowd. Since \( k \) and \( j \) belong to a continuum of managers, they only meet once. Therefore, one does not need to carry the whole history of a given manager—only her current number \( n^l_t \) of ideas is relevant.

When \( k \) and \( j \) run into each other, they truthfully exchange their entire set of ideas. The reason is that managers, being part of a crowd, meet at most once and cannot individually influence prices—they have no incentives to lie.\textsuperscript{22} Heuristically, one can think of truth-telling as follows. Kosowski, Timmermann, Wermers, and White (2006) show that active management skills not only generate higher performance but also superior cost efficiencies. This evidence can be combined with the result of Stein (2008)—competitors choose to share their information if more information generates

\begin{itemize}
\item \textsuperscript{20}See Colla and Mele (2010) for a cyclical network, Acemoglu, Bimpikis, and Ozdaglar (2010) for an endogenous network structure and DeMarzo, Vayanos, and Zwiebel (2003) for results sensitivity regarding the network specification.
\item \textsuperscript{21}See, Hong, Hong, and Ungureanu (2010) who use such models to explain the dynamics of trading volume and Burnside, Eichenbaum, and Rebelo (2010) who model the booms in the housing market.
\item \textsuperscript{22}Agents do not attempt to hide part of their information, nor to add noise to their set of ideas. Strategic considerations only enter in networks comprised of a finite number of agents.
\end{itemize}
lower costs, which induces strategic complementarity.\textsuperscript{23}

As an immediate consequence, information sharing is \textit{additive-in-types}. Suppose \(k\) and \(j\) respectively have \(n - m\) and \(m\) ideas; then they both wind up with \(n\) ideas, after they meet. “Good” ideas—large numbers of ideas—may thereby diffuse over the \textit{whole} network of managers, an outcome I precisely want to avoid. I define “good” ideas as those composed of \(K (\geq 2)\) or more pieces of information.\textsuperscript{24} To keep good ideas local, I assume that the crowd of managers \(l\) splits after managers gather \(K\) or more ideas. As the crowd splits, two networks of managers arise, Network \(A\) and \(B\). Managers of Network \(A\) do not talk to those of Network \(B\) (and vice-versa).

Network \(A\) is a network in which “cheap talk” takes place. Managers positioned within this network have at least their own working idea, yet do not hold good enough ideas—less than \(K\)—to be part of Network \(B\). Therefore, conversations in this network may only deliver an incremental number \(m \sim \mu^A/q^A\) of ideas that takes values on the support \([1, K - 1]\). The goal is to determine how the distribution \(\mu^A\) of ideas within Network \(A\) behaves over time. An important observation is then needed: Network \(A\) has its own endogenous size \(q^A = \sum_{n=1}^{K-1} \mu^A(n)\) and, since managers are bound to meet others of their own network, the actual probability that managers meet someone (in \(dt\)) is \(\eta q^A dt\). This probability represents how likely it is that managers meet someone at all, times the size of the group of managers they are restricted to meet. I adapt the Boltzmann’s Stosszahlansatz equation for \(\mu^A\) in Duffie and Manso (2007) accordingly and highlight the result in the proposition below.

\textbf{Proposition 1.} Let \(\mu^A_t(A) = \iota \{j : j_t \in A\}\) be the cross-sectional distribution of managers in Network \(A\) where \(A = \{1, \ldots, K - 1\}\) and \(A \subseteq A\). Let \(q^A_t = \sum_{n=1}^{K-1} \mu^A_t(n)\) be the mass of managers in Network \(A\). For any \(n \in A\), \(\mu^A(\cdot)\) obeys

\[
\frac{d}{dt} \mu^A_t(n) = -\eta q^A_t \mu^A_t(n) + \eta \sum_{m=1}^{n-1} \mu^A_t(n - m) \mu^A_t(m)
\]  

(5)

with initial conditions \(\mu^A_0(n) = \delta_1\) where \(\delta_1\) is a Dirac mass at \(n = 1\).

\textbf{Proof.} See Appendix A. Q.E.D.

Meetings have two effects on the evolution of the distribution of ideas in Network \(A\). First, meetings cause managers to change their type, the first term in (5). Specifically, suppose a manager currently holds \(n\) ideas. As she meets someone, she gets \(m\) new ideas and no longer holds \(n\) ideas. If she ends up with \(K\) or more ideas after the meeting, she enters Network \(B\). Otherwise, she stays in Network \(A\). Second, since

\textsuperscript{23}Acemoglu, Bimpikis, and Ozdaglar (2010) show that truth-telling can be an equilibrium outcome.

\textsuperscript{24}See the NBER version of Stein (2007), p. 6-7, for an example related to arbitrage.
social dynamics are additive-in-types, if a meeting delivers $m$ incremental ideas, it must be that a manager formerly held $n - m$ ideas for her to wind up with $n$ ideas after the meeting. The second term in (5) accounts for all such possible meetings.

**Figure 1: Evolution of Cross-Sectional Densities**

Evolution of the Social Network (Part I). Figure 1 depicts the cross-sectional distribution $\mu_t$ of the number $n_t$ of ideas at time $t = 1$, $t = 2$ and $t = 3$, each corresponding to a given row. The leftmost and center columns correspond, respectively, to the distribution of ideas within Network $A$ (\(\bullet\)) and Network $B$ (\(\square\)). The rightmost column represents the mass of managers $i$ (\(\oplus\)). The social intensity is $\eta = 3$ and the switching thresholds are $K = 10$ and $N = 30$.

The evolution of the distribution $\mu^A$ is illustrated in Figure 1. Managers having met no one yet—those solely holding their working idea—initially represent the largest fraction of Network $A$. They progressively become a minority as more and more managers eventually meet someone. In turn, the size $q^A$ of Network $A$ decreases over time, as meetings cause some managers to develop good ideas—$K$ or more—and thus to migrate to Network $B$ (see Figure 2).

I view Network $B$ as a community of knowledgeable, privileged managers who only exchange valuable ideas. Managers in this network can potentially carry a considerable number of ideas, another outcome I would like to rule out. In the present context, it is difficult to attribute an economic meaning to hundreds of ideas exchanged, whereas “perfect” information is naturally interpreted as insider information. I thus assume that managers eventually gain perfect knowledge of $\Pi$ after collecting $N(\geq 2K)$ ideas. As a result, the cross-sectional distribution $\mu^B$ of ideas in Network $B$ lies on $[K, N - 1]$. 

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Evolution of the Social Network (Part II). Figure 2 depicts the evolution of the mass $q_t$ of each network from time $t = 0$ to $t = 10$. The leftmost and center figures show the mass of Network $A$ and $B$, respectively. The rightmost figure shows the mass of managers $i$. The social intensity is $\eta = 3$ and the switching thresholds are $K = 10$ and $N = 30$.

As managers become perfectly informed, they do not further communicate—they leave Network $B$. Insider information therefore does not circulate and the fraction of informed managers $i$ is thereby endogenized. It increases over time as seen in Figure 2.

The dynamics of $\mu^B$ are reported in Proposition 2 below, which also summarizes how managers’ number $n^i_l$ of ideas evolves. The distribution $\mu^B$ behaves similarly to $\mu^A$—Network $B$ also has its own endogenous size $q^B = \sum_{n=K}^{N-1} \mu^B_t(n)$ and the probability of meeting someone in this network (in $dt$) is $\eta q^B_t dt$. Yet, $\mu^B$ further accommodates the migration of managers who develop good ideas, the first term in the bracket in (6).

**Proposition 2.** Let $\mu^B_t(B) = \iota(\{j : j_t \in B\})$ be the cross-sectional distribution of managers in Network $B$ where $B = \{K, \ldots, N - 1\}$ and $B \subseteq B$. Let $q^B_t = \sum_{n=K}^{N-1} \mu^B_t(n)$ be the mass of managers in Network $B$. For any $n \in B$, $\mu^B_t(\cdot)$ obeys

$$\frac{d}{dt} \mu^B_t(n) = -\eta q^B_t \mu^B_t(n) + \eta \left( 1_{\{n \in [K, 2(K - 1)]\}} \sum_{m=n-(K-1)}^{K-1} \mu^A_t(n-m) \mu^A_t(m) + 1_{\{n \in [2K, N-1]\}} \sum_{m=K}^{n-K} \mu^B_t(n-m) \mu^B_t(m) \right) \tag{6}$$

with initial conditions $\mu^B_t(0) = \delta_0$ where $\delta_0$ is a Dirac mass at $n = 0$. The mass of managers $i$ is given by $1 - \omega_t = 1 - q^A_t - q^B_t$. Overall, the Poisson counter $(N^l_t)_{t \geq 0}$ jumps with intensity $\eta_t \equiv \eta(q^A_t 1_{\{n^l_t \in A\}} + q^B_t 1_{\{n^l_t \in B\}})$. The incremental number $m_t$ of ideas is either drawn from $m_t \sim \mu^A_t / q^A_t$ or $m_t \sim \mu^B_t / q^B_t$ and the number $n^l_t$ of ideas evolves as

$$dn^l_t = \left( m_t 1_{\{m_t + n^l_t \in A \cup B\}} + \infty 1_{\{m_t + n^l_t \notin A \cup B\}} \right) dN^l_t, \quad n^l_0 = 1.$$

**Proof.** See Appendix A. Q.E.D.
Interestingly, Figure 2 shows that the size $q^B$ of Network B moves non-monotonically. Network B is initially empty, as managers are either part of Network A or perfectly informed. As information starts to percolate, Network B is fed with migrating managers—good ideas stay local. After a while, managers who collect $N$ ideas become perfectly informed and leave Network B (they have no incentives to further talk), ultimately causing the size of Network B to fall—insider information does not circulate. The distribution $\mu^B$ follows the same pattern. Figure 1 shows that $\mu^B$ has two parts, which respectively represent migrating managers and incumbents to Network B. The fraction of migrating managers progressively decreases as its source—Network A—dries up, while the fraction of incumbents first increases and then decreases.\textsuperscript{25} The social dynamics in Angeletos and La’O (2012) share a similar feature.

3 Equilibria with Word-of-Mouth Learning

The setup being now established, I can compute its equilibria. I first $i)$ derive fund managers’ learning process in the presence of social interactions (Subsection 3.1). Second, following somewhat standard steps, $ii)$ I solve managers’ optimization problem and $iii)$ impose that markets clear (Subsection 3.2).

3.1 Word-of-Mouth Learning

Social interactions give rise to a novel form of learning. This subsection shows that learning can be neatly split into what managers learn from the tape—the public channel—and what they learn from conversations—the private channel. The pattern of information arrival is as follows. Information extracted from the price flows tick-by-tick, producing small and frequent updates in managers’ estimates—in my model, these updates are continuous. For most managers, private conversations seldom take place. But upon meeting someone, managers obtain large pieces of information and significantly update their expectations—in my model, these updates are discontinuous. Updates ultimately feed back into prices and increase price informativeness.

I start by recalling that fund managers $l$, those imperfectly informed, attempt to forecast $\Pi$, the fundamental part subject to learning. They do so based on their own information $\mathcal{F}^l$ and come up with an estimate $\hat{\Pi}_t^l \equiv E[\Pi|\mathcal{F}_t^l]$ and a variance $\sigma_t^l \equiv V[\Pi|\mathcal{F}_t^l]$ at any time $t$. This task is affected by the presence of noise traders through the supply $\Theta$ of the stock, for which they also need an estimate $\hat{\Theta}_t^l \equiv E[\Theta|\mathcal{F}_t^l]$.

\textsuperscript{25}If one chooses to set $N = 2K$, then one precludes meetings among incumbents and managers immediately achieve type $i$ as soon as they meet someone in Network B.
Managers build their knowledge $\mathcal{F}^l$ from two sources: first, social interactions bring about valuable insights in the form of a set of ideas $\{S^l_k\}_{k=1}^{n^l}$. This is precisely the novel aspect of learning in my model—word-of-mouth communication. Second, the price $P$ aggregates information that is dispersed across managers. This well-known learning channel is strongly present in my model. Managers analyze the price in an attempt to infer conversations among other managers. Combining these two sources of information, a manager holding $n^l$ ideas observes

$\mathcal{F}^l_t = \sigma \left( (P_s, S^l_k, n^l_s) : 0 \leq s \leq t, k \leq n^l_s \right), \quad 0 \leq t < T.$ \hspace{1cm} (7)

My goal is to relate managers’ performance to empirical findings. Since empiricists—henceforth, the econometrician—only observe market information, I need to consider this set as well, $\mathcal{F}^c_t = \sigma(P_s : 0 \leq s \leq t)$. Market information is common and is denoted by $c$. Econometrician’s estimates are denoted by $\hat{\Pi}^c$ and $\hat{\Theta}^c$ and her variance by $\sigma^c$.

Perhaps needless to say, managers $i$ do not learn about $\Pi$, since they observe it. Hence, their information is summarized by

$\mathcal{F}^i_t = \sigma((P_s, \Theta_s) : 0 \leq s \leq t) \lor \sigma(\Pi), \quad 0 \leq t < T.$ \hspace{1cm} (8)

Inspecting (8), one may be surprised that managers $i$ observe the supply history $(\Theta_t)_{t \geq 0}$. But since I focus the analysis on linear equilibria (defined below), a common practice in the literature, managers $i$ can readily invert the price and observe the supply.\hspace{1cm} 26,27

**Definition 1.** In a linear equilibrium, the stock price function has the following form:

$P_t = \lambda_{1,t}\Pi + (1 - \lambda_{1,t})\hat{\Pi}^c_t + \lambda_{2,t}\Theta_t$ \hspace{1cm} (9)

over $[0, T)$, where $\lambda_{1,t}$ and $\lambda_{2,t}$ are deterministic functions and $P_T = \Pi + \delta$.

Focussing on linear equilibria considerably facilitates the analysis of the model, yet linear equilibria do not directly obtain in my setting. The combination of continuous-time trading and word-of-mouth learning generally leads to intractable equilibria. In Subsection 3.2, I show that it only takes a simple and accurate approximation of managers’ portfolio for Definition 1 to apply.\hspace{1cm} 26

---

26 $\mathcal{F}$ represents the filtration generated by $(P_t, \Theta_t, \Pi)$ for agents $i$ and by $(P_t, \{S^l_k\}_{k=1}^{n^l})$ for an agent $l$ who holds $n^l$ signals at time $t$. Also, since an infinite number of ideas is tantamount to perfect knowledge of $\Pi$, (8) is obtained from (7) by letting $n^l \rightarrow \infty$.

27 The CARA utility specification in (2) yields asset demands that do not depend on agents’ wealth and allows to restrict the analysis to linear price functions. See Grossman and Stiglitz (1980) and the references thereof. See Breon-Drish (2011) for an analysis of nonlinear equilibria.
Linear prices in (9) have two parts.\footnote{Prices do not depend on private ideas. Aggregating over the crowd of managers $l$, the law of large numbers ensures that the average of all private ideas reveals $\Pi$—ideas get washed out in the aggregate.} The first part, $\lambda_1\Pi + (1 - \lambda_1)\hat{\Pi}^c$, represents average market expectations about the present value of future dividends $\Pi + \delta$, conditional on perfect information, and discounted at the risk-free rate $r = 0$.\footnote{See, for instance, Campbell and Kyle (1993) or Hong and Wang (2000) and Appendix E.} It corresponds to the price that would obtain if managers were risk-neutral.

**Figure 3: Price Coefficients and Price Informativeness**

**Price Coefficients, Price Informativeness and Common Uncertainty.** Figure 3 plots the evolution of the price coefficients $\lambda_1$ and $\lambda_2$ in Panels A and B, respectively, common uncertainty $\sigma^c$ in Panel C, and the speed $k$ of information propagation through prices in Panel D. Each is plotted for the cases of no social interaction (-----), a social interaction of two meetings per year (-----), one meeting per quarter (- - -) and one meeting every two months (----). The calibration is reported in Table 1.

Importantly, the behavior of $\lambda_1$ (depicted in Panel A of Figure 3 as a function of time and social interactions $\eta$) shows that *word-of-mouth communication increases price informativeness*. The weight $\lambda_1$ tilts average market expectations either towards common expectations $\hat{\Pi}^c$ or towards the actual $\Pi$ and its evolution is driven by the market learning process. In an economy absent of social interactions ($\eta = 0$), average
market expectations are strongly biased towards common beliefs and prices reveal little information about \( \Pi \). As social interactions intensify \((\eta > 0)\), prices convey more information, the market learning process significantly improves, and average market expectations shift closer to \( \Pi \). Price informativeness increases as social interactions cause both the fraction of managers \( i \) and managers’ average precision to rise.

Because managers are risk-averse, they want to be compensated for the aggregate risk \( \Theta \) they have to bear. The second term in (9), \( \lambda_2 \Theta \), acts as a discount on the price (through \( \lambda_2 < 0 \)), which increases expected stock returns. The evolution of \( \lambda_2 \) is the result of two opposite forces. On the one hand, the more fiercely managers speculate, the larger is the risk to be taken advantage of by better-informed managers—the compensation for risk \( |\lambda_2| \) rises. On the other, the more fiercely managers speculate, the more information is revealed through prices—the compensation for risk falls. Social interactions cause the latter effect to initially dominate (see Panel B). Yet, residual uncertainty remains unknown until the announcement date and the risk associated with its revelation gives rise to an increase in \( |\lambda_2| \) around \( T \).

At the announcement date, everyone discovers the fundamental value \( \Pi + \delta \). In turn, a jump occurs in managers’ information sets to include \( \Pi \) and \( \delta \) as part of public information.\(^{30}\) This jump determines how the price behaves when the stock pays out.

Prices having the linear form in (9), I can show how managers \( l \) and the econometrician (with common information \( c \)) dynamically update their estimates of \( \Pi \) and \( \Theta \). I gather these dynamics in Proposition 3, a proof of which may be found in Appendix B.

**Proposition 3.** In a linear equilibrium, conditional expectations solve the SDEs:

\[
\begin{align*}
 d \begin{bmatrix} \hat{\Pi}_t^c \\ \hat{\Theta}_t^c \end{bmatrix} &= \begin{bmatrix} 0 & 0 \\ 0 & -a_\Theta \end{bmatrix} \begin{bmatrix} \hat{\Pi}_t^c \\ \hat{\Theta}_t^c \end{bmatrix} dt + \begin{bmatrix} 0 \\ \sigma_\Theta \end{bmatrix} \begin{bmatrix} \delta_i k_i \\ \Theta_i \end{bmatrix} d\hat{B}_t^c, \\
 d \begin{bmatrix} \hat{\Pi}_t^l \\ \hat{\Theta}_t^l \end{bmatrix} &= \begin{bmatrix} 0 & 0 \\ 0 & -a_\Theta \end{bmatrix} \begin{bmatrix} \hat{\Pi}_t^l \\ \hat{\Theta}_t^l \end{bmatrix} dt + \begin{bmatrix} 0 \\ \sigma_\Theta \end{bmatrix} \begin{bmatrix} \delta_i (n_{t-}^l) k_i \\ \Theta_i \end{bmatrix} d\hat{B}_t^l + \begin{bmatrix} 1 \\ -\frac{1}{\lambda_{1,t}} \end{bmatrix} Z_{m,t}^l dN_t^l 
\end{align*}
\]

with

\[
k_t = \frac{1}{\sigma_\Theta \lambda_{2,t}^2} (\lambda_{1,t} \lambda_{2,t} - \lambda_{1,t} (\lambda_{2,t} - a_\Theta \lambda_{2,t}))
\]

and \( Z_{m,t}^l \equiv \frac{S_{m,t} - \bar{S}_{l}^l}{\sigma_{z_{l}}^2 / m_{t}} d\hat{B}_{t}^l \). \((\hat{B}_t^c)_{t \geq 0} \) and \((\hat{B}_t^l)_{t \geq 0} \) are one-dimensional Brownian motions with respect to \( \mathcal{F}_t^c \) and \( \mathcal{F}_t^l \). \( \bar{S}_{l}^l \equiv \frac{1}{m_{t}} \sum_{k=1}^{m_{t}} S_k \) denotes a sequence of ideas accruing from a conversation that delivers \( m \) incremental ideas and \( Z_{m,t}^l \) denotes the jump occurring

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\(^{30}\)At time \( T \), the information set of an agent \( l \) is given by \( \mathcal{F}_{T}^c = \mathcal{F}_{T-}^c \cup \sigma(\Pi, \delta) \). The same goes with both \( \mathcal{F}_{T}^l = \mathcal{F}_{T-}^l \cup \sigma(\Pi, \delta) \) and \( \mathcal{F}_{T} = \mathcal{F}_{T-} \cup \sigma(\delta) \). I refer the reader to Appendix E.

16
in conditional expectations as this new information is processed. The variances, $\sigma^2_t$ and $\sigma_t^2$, of the respective filters

$$
d\sigma^2_t = -k^2_t(\sigma^2_t)^2 dt, \quad d\sigma_t^2(n_t^l) = -k^2_t(\sigma_t^2(n_t^l))^2 dt - \frac{1}{\sigma_S^2} \sigma_t^2(n_t^l)\sigma_t^2(n_t^l) m_t dN_t^l
$$

obey the relation $\frac{1}{\sigma_t^2(n_t^l)} = \frac{1}{\sigma_t^2} + \frac{n_t^l}{\sigma_S^2}$. 

**Proof.** See Appendix B. Q.E.D.

This proposition shows that the dynamics of managers’ expectations in (11) involve a continuous part pertaining to the observation of prices and a discontinuous part associated with meetings, while common views in (10) are purely continuous. In Figure 4 below, I attempt to illustrate this pattern of information arrival by simulating a manager $l$’s number $n_t^l$ of ideas (Panel A), her variance $\sigma_t^2$ (Panel B) and her informational advantage $\Pi_t^l - \Pi_t^c$ (Panel C). In periods during which manager $l$ does not meet anyone (that is, the flat parts in Panel A), she analyzes the tape in light of the conversations she had. To her mind, every price change possibly reveals other managers’ information. This kind of information flows tick-by-tick. For this reason, when manager $l$ is not socially active, her views $\Pi_t^l$ are smooth. Therefore, her informational advantage $\Pi_t^l - \Pi_t^c$ behaves similarly to common views $\Pi_t^c$, as seen in Panel C.

**Figure 4: A Simulated Path**

---

**Simulated Path of the Filter.** Figure 4 plots, for an arbitrary agent $l$, a simulated path of her number $n_t^l$ of ideas in Panel A, her individual $\sigma_t^2$ (-----) and the common $\sigma_t^2$ (-----) posterior variance in Panel B, and her informational advantage $\Pi_t^l - \Pi_t^c$ (-----) along with the common filter $\Pi_t^c$ (-----) in Panel C. The social intensity is set to one meeting every two months on average, $\eta = 6$. The calibration is reported in Table 1.

Now, due to noise trading, manager $l$ knows the price only partially reflects conversations among other managers. In that respect, private discussions offer an alternative
channel conveying additional information. As manager \( l \) runs into someone, she gets \( m \) new ideas and, as is visible in Panel A, her number of ideas steeply increases. At these particular points in time, her informational advantage is seen (from Panel C) to experience significant jumps as she processes the new insights collected, i.e., her set \( \bar{S}_n^l = \{S^l_k\}_{k=1}^{n'} \) of ideas is suddenly augmented. These spikes only appear when she is socially active. Otherwise, her set \( \bar{S}_n^l \) of ideas does not change. In contrast, common views remain smooth as common information is continuously extracted from the price.

This description neglects another important aspect of social learning in my model. A manager \( l \) not only updates her views, she also becomes more precise. As her views, her precision—the inverse of her variance \( \sigma^l \)—directly relates to private meetings and public information. Consider first the effect of private meetings on her precision. Every meeting (in Panel A) maps into exactly one downward jump in her variance (in Panel B). Because manager \( l \) holds at least one idea, her variance always lies below that of the econometrician \( \sigma^c \) (the dashed line in Panel B). Each meeting further reduces her variance \( \sigma^l \) and, as she makes her way to Network \( B \) (when \( n^l \) crosses \( K \) in Panel A), her views (in Panel C) become significantly less volatile. After two meetings within Network \( B \), she eventually gains perfect knowledge of \( \Pi \). As a result, \( \sigma^l \) drops to zero (as seen in Panel B), her expectations hit \( \Pi \) and her informational advantage, now given by \( \Pi - \hat{\Pi}^c \), moves in a direction opposite to that of \( \hat{\Pi}^c \) (in Panel C).

Second, consider the effect of public information on her precision. When she only analyzes the price, her variance decays deterministically according to (13). During such times, the evolution of her precision is driven by a key variable, \( k \). One can view \( k \) in (12) as controlling the speed at which information is revealed through prices. To see this, notice that (12) may be rewritten as

\[
k_t = \frac{1}{\sigma^\Theta} \left( \frac{d}{dt} \lambda_{1,t} + a^{\Theta} \frac{\lambda_{1,t}}{\lambda_{2,t}} \right).
\]

If the ratio \( |\lambda_{1,t}/\lambda_{2,t}| \) is large, prices are more sensitive to information and, therefore, more informative. The evolution of \( k \), plotted in Panel D of Figure 3, corroborates an important observation previously made—social interactions vastly increase price informativeness and make technical analysis more effective. As a result, the market learning process improves at great speed and common uncertainty \( \sigma^c \) (in Panel C) is significantly reduced. The reason is that managers speculate more aggressively, for the more intense interactions are, the more they rush to speculate (see Subsection 6.2).
3.2 Optimal Portfolio Choice and Market Clearing

Managers’ trading serves two purposes: managers simultaneously act as market makers by providing liquidity to noise traders and speculate on the basis of their set of ideas. Equation (14) below makes these two trading motives apparent:

\[
\theta_t^l = d^l_{\Theta,t} \hat{\Theta}_t + d^l_{\Delta,t} (\hat{\Pi}^l_t - \hat{\Pi}^c_t) = d^l_{\Theta,t} \Theta_t + d^l_{\Delta,t} \lambda^l_t (\Pi - \hat{\Pi}^l_t) + d^l_{\Delta,t} \frac{\sigma^2_{\Pi} + \sigma_\delta^2 n_t^l (\bar{S}^l_t - \hat{\Pi}^l_t)}{\lambda^l_2} \quad \text{(14)}
\]

A manager’s positions \(\theta^l\) reflect a balance between her market-making activity, \(d^l_{\Theta}\), and her speculative activity, \(d^l_{\Delta}\).

The expression for market-making in (14) carries a central insight—managers’ market-making activity is obscured by the inference problem they face, namely that they need to distinguish trades posted by noise traders from those posted by better-informed managers. To their mind, a change in prices has two possible interpretations. One possibility is that noise traders’ demand varied; then, managers provide the required liquidity by adjusting \(d^l_{\Theta}\) while keeping their speculative positions \(d^l_{\Delta}\) unchanged. Alternatively, other managers may have received new information. If so, managers first readjust their speculative positions, since they probably misevaluated \(\Pi\). Second, they reduce their market-making positions (through \(d^l_{\Delta} \lambda^l_1 \lambda^l_2 (\Pi - \hat{\Pi}^l)\), since \(\lambda_2 < 0\)) to minimize the chance that they end up on the wrong side of the trade.

This intuition does not apply to managers \(i\), who know \(\Pi\). Being the best-informed managers in the economy, they do not hedge against others’ trades and the second expression in (14) reduces to \(d^l_{\Theta} \Theta + d^l_{\Delta} (\Pi - \hat{\Pi}^c)\). As a result, managers fully exploit their informational advantage, \(\Pi - \hat{\Pi}^c\). While managers also exploit their informational advantage \(\bar{S}^l_t - \hat{\Pi}^c\), they need to mitigate their market-making positions.

Portfolios in (14) result from an approximation. This approximation, which allows me to focus the analysis on linear equilibria (described in Definition 1), proceeds as follows.\(^{32}\)

Suppose that there exists another asset with price \(X^l\) and dynamics \(dX^l_t = -\eta_t dt + dN^l_t\). By trading this asset, managers can hedge the risk associated with their meetings. In turn, the traditional conjecture for their value function \(V^l\)

\[
V^l(W^l, \Psi^l) = -\exp \left( -\gamma W^l - \frac{1}{2} (\Psi^l)^T M^l \Psi^l \right), \quad (15)
\]

which is exponential-quadratic in the state variables \(\Psi^l\) of their problem, obtains.\(^{33}\)

\(^{31}\)See Proposition 4 and Appendix F.2 for a derivation.

\(^{32}\)An approximation is needed due to continuous trading. It is one of the kind implemented in Duffie, Gârleanu, and Pedersen (2007). See also Appendix E.2 in Vayanos and Weill (2008).

\(^{33}\)The demonstration is provided in Appendix D.
reason is that managers l build a position \( \psi^l_t = \frac{1}{\gamma} \log \frac{V^l_t}{V^l_{t-}} + W^l_t - W^l_{t-} \) in asset \( X^l \) that exactly offsets the jump in their value function upon meeting someone. Without this asset, they cannot prevent the state variables \( \Psi^l \) to cause a quadratic jump in (15), which precludes a tractable solution to their problem.

Yet, if one performs a linearization—a first-order expansion around \( \psi^l_t \approx 0 \)—of the jump size in managers’ value function, one may use the usual conjecture in (15). Following Haugh, Kogan, and Wang (2006), I verify that this approximation is accurate.\(^{34}\) Proposition 4 below shows that managers’ portfolios have the form in (14).

**Proposition 4.** A fund manager \( l \) holding \( n^l_{t-} \) ideas at time \( t \) builds an approximately optimal portfolio strategy \( \theta^l_{t-} = \theta^l(\tilde{\Theta}^l_{t-}, \tilde{\Pi}^c_{t-} - \tilde{\Pi}^c_{t-}, n^l_{t-}, t) \) given by

\[
\theta^l_{t-} = A_{Q,t}^l - B_{Q,t}(B_{\Psi^l,t}^{*l}(n^l_{t-}))^\top M^{*l}(n^l_{t-}, \phi^{*l}_{2,t-}) \frac{\tilde{\Theta}^l_{t-}}{\gamma B_{Q,t}^2} \left( \tilde{\Pi}^c_{t-} - \tilde{\Pi}^c_{t-} \right) \tag{16}
\]

where \( M^{*l}(n^l_{t-}, \phi^{*l}_{2,t-}) \) is a \( 2 \times 2 \)—matrix of coefficients that solves the matrix differential equation in (52) with boundary condition given in (57) and where \( A_{Q,t}^l, B_{Q,t} \) and \( A_{\Psi,t}^l \) are deterministic coefficients and \( B_{\Psi^l,t}^{*l}(n^l_t) \) is a coefficient depending on the number \( n^l_t \) of ideas held by agent \( l \). The coefficient \( \phi^{*l}_{2,t-} \) is network-specific and given by

\[
\phi^{*l}_{2,t-}(M^{*l}) = \left\{ \begin{array}{ll}
\sum_{m \in A} \mu^A_t(m) \left( M^{*l}(n^l_{t-} + m) - M^{*l}(n^l_{t-}) \right) & \text{if } n^l_{t-} \in A \\
\sum_{m \in B} \mu^B_t(m) \left( M^{*l}(n^l_{t-} + m) - M^{*l}(n^l_{t-}) \right) & \text{if } n^l_{t-} \in B \end{array} \right. \tag{17}
\]

**Informed fund managers i build optimal stock holdings given by**

\[
\theta^i_t = \theta^i(\Theta_t, \Pi - \tilde{\Pi}^c_t, t) = A_{Q,t}^l - B_{Q,t}(B_{\Psi^i,t}^{*l}(n)) \frac{\Theta_t}{\gamma B_{Q,t}^2} \Pi - \tilde{\Pi}^c_t \tag{18}
\]

where \( M^{*i} \) is a \( 2 \times 2 \)—matrix of coefficients that solves the matrix differential equation in (51) with boundary condition given in (58) and where \( B_{\Psi^i,t}^{*l} = \lim_{n \to \infty} B_{\Psi^i,t}^{*l}(n) \).

**Proof.** See Appendix C. Q.E.D.

Proposition 4 also shows that managers anticipate that their information set may be augmented as the result of future conversations. If they meet someone, they revise

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\(^{34}\)I do so in Appendix D, which contains a formal derivation as well as an upper bound on the approximation error. Simulations show that the upper and lower bounds on the initial value function are of the magnitude -0.43 and -0.41 for the range of parameters considered. This implies a relative error of less than 5%. 

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their current opinion through the term $\phi_2$ in (17). This term captures the impact of word-of-mouth learning and accounts for the common knowledge of the network structure—managers $i$ and those in Network $A$ and $B$ know their relative informational (dis)advantage. Hence, $\phi_2$ determines how they speculate on their own information $\tilde{S}^l - \tilde{\Pi}^c$ and how they hedge against informed managers’ information $\Pi - \tilde{\Pi}^l$ in (14).

Finally, prices need to reflect that managers interact in a general equilibrium framework. Proposition 5 verifies that prices clear the market.

**Proposition 5.** Given the optimal portfolio strategies in (16) and (18), the stock price has the linear form in (9) where the equilibrium price coefficients satisfy the differential equations in (76) and (77) with boundary conditions in (78) and (79).

**Proof.** See Appendix E. Q.E.D.

### 3.3 Equilibrium Implementation and Calibration

Propositions 3, 4 and 5 jointly define a system of equations whose boundary conditions depend on the terminal level $\sigma_{f_{\text{L}}}^0$ of common uncertainty, which is unknown. I thus need to guess a value for $\sigma_{f_{\text{L}}}^0$ and then shoot towards the initial condition $\sigma_0^2$. Depending on the meeting intensity $\eta$ and residual uncertainty $\delta$, three equilibria are obtained for a certain range of the parameter space. One of these equilibria may be immediately discarded, though. It is an equilibrium in which the volatility of prices is constantly null and the price thus fully reveals $\Pi$—managers do not trade.

Other equilibria originate from the interaction between common uncertainty $\sigma^c$ and $k$ in (12), which, I recall, captures price informativeness. Since social interactions increase price informativeness, they increase $|k|$, which causes $\sigma^c$ (in Panel C of Figure 3) to substantially drop through (13) as the result of the learning improvement. This feedback may eventually give rise to two equilibria—for $\sigma_0^2$ given, two levels of terminal uncertainty $\sigma_{f_{\text{L}}}^0$ may obtain depending on $k$ and, thus, on whether or not managers speculate fiercely.

Following this intuition and Grundy and McNichols (1989), these

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35$\phi_2$ plays an analogous role to the quadratic term in Wang (1993) where learning is purely Brownian.
36Since both boundary conditions in (78) and (79) depend on $\sigma_{f_{\text{L}}}^0$ which is unknown, a shooting procedure is needed. The system of equations may be solved using a standard finite-difference scheme such as Runge-Kutta. For instance, the NDSOLVE function of Mathematica proves to work well with the StiffnessSwitching option. In doing so, it is convenient to make the system of equations in (52), (76) and (77) explicit. Appendix E shows how to proceed.
37Residual uncertainty is often a cause of equilibrium multiplicity: Grundy and McNichols (1989) show that multiplicity obtains in their setting if residual uncertainty lies within a certain range. In particular, Hirshleifer, Subrahmanyam, and Titman (1994) obtain four equilibria. He and Wang (1995) further argue that multiplicity may not arise if $a_0$ is sufficiently large.
38I show this at the end of Appendix E.
39This may be illustrated by means of a phase diagram.
equilibria may be ranked according to $|\lambda_1 - \lambda_2|$. Note that equilibrium uniqueness can be enforced by increasing residual uncertainty $\sigma_\delta$, which tames the magnitude of trading.

I base the equilibrium selection on a well-established fact: the empirical literature widely documents the superior performance of aggressive growth funds. For instance, Barras, Scaillet, and Wermers (2010) find that aggressive growth funds have the highest proportion of skilled managers. Hence, I pick the equilibrium in which speculation is the most aggressive—speculative activity $d_\Delta$ is the highest. This equilibrium is often referred to as the high volatility equilibrium. For this equilibrium to obtain and managers to trade aggressively, residual uncertainty needs to be sufficiently low. For this reason, I set $\sigma_\delta$ below that used in He and Wang (1995) (see Table 1).

I consider an horizon date of one year, a relatively short-term horizon. I let the initial fraction $\omega_0$ of fund managers $l$ be 1 so that every manager is initially located in Network $A$. Hence, managers start with one idea and become heterogeneously informed

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<tr>
<th>Description</th>
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<th>Value</th>
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</tr>
<tr>
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</tr>
<tr>
<td>Initial Proportion of Informed Managers</td>
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<td>0</td>
</tr>
<tr>
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</tr>
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</tr>
<tr>
<td>Supply Volatility</td>
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</tr>
<tr>
<td>Volatility of Dividend II</td>
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</tr>
<tr>
<td>Volatility of the Signal</td>
<td>$\sigma_S$</td>
<td>$\sqrt{2}$</td>
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<td>Perfect Knowledge Threshold</td>
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</tr>
<tr>
<td>Good Ideas Stay Local Threshold</td>
<td>$K$</td>
<td>5</td>
</tr>
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### Table 1: Parameters Calibration

The calibration includes all the parameters that shall be maintained constant for the analysis, some of which are borrowed from Campbell and Kyle (1993), Wang (1993) and He and Wang (1995). The table does not include a calibration for $\eta$ as the latter shall be varied for the purpose of the analysis.


See Banerjee (2010) who describes multiple equilibria often referring to high and low volatility equilibria. The author argues that these equilibria have both desirable theoretical and empirical properties. See also Spiegel (1998) and Watanabe (2008).

In this particular case, letting $\sigma_S \to \infty$ may introduce some instability in the information structure: the equilibrium may abruptly change in the neighborhood of $t = 0$, for the limiting equilibrium as $\omega_0 \to 1$ can be different from the one that prevails when $\omega_0 = 1$. This stems from the abrupt collapse in the informational content of prices as $\omega_0$ reaches 1. Yet, as long as $\sigma_\delta < \infty$, differential information makes the information structure not purely hierarchical and trading is entertained by residual uncertainty even if investors only receive a single private signal, as shown in He and Wang (1995). This rules out the type of instability pointed out by Wang (1993).
as soon as they start to interact.

Managers’ absolute risk aversion is set below 1 to reflect that, as institutional investors, they exhibit a fairly high tolerance towards risk. The remainder of the calibration is adapted from Campbell and Kyle (1993), Wang (1993) and He and Wang (1995) and is chosen to be consistent with empirical estimates (see Appendix G).

4 Market-Timing Ability and Performance

Can mutual fund managers time the market? This question has been under intense empirical investigation at least since Treynor and Mazuy (1966) and Henriksson and Merton (1981). These early studies develop linear regression models of the CAPM-type including an additional convex term reflecting timing skills. Doing so, they conclude in favor of the Efficient Market Hypothesis (see also Henriksson (1984)). These studies have largely contributed to the view that managers do not exhibit timing skills. Subsequent works have extensively attempted to refine early timing models by addressing certain practical issues, causing timing abilities to appear somewhat more nuanced.43

The empirical literature has been equally inconclusive as to the performance and the ranking of managers. A host of empirical studies, starting with Jensen (1968) and later followed by Carhart (1997), find that most mutual funds fail to outperform, and often underperform, passive benchmarks, even before transactions costs.44 In contrast, alternative investigations (e.g., Grinblatt and Titman (1992) and Hendricks, Patel, and Zeckhauser (1993)) conclude that outperformance may persist, yet not accounting for trading costs. In general, the empirical consensus is that performance does not persist, except for a small group of funds (e.g., aggressive-growth funds) whose performance is yet relatively short-lived.45

This section offers a theoretical mechanism rationalizing why timing skills seem to be weak and performance not to be persistent. In my model, the traditional measure of

43Time-varying betas have been introduced (Ferson and Schadt (1996)), the dichotomy between the rebalancing and observation frequency of holdings has been accounted for (Goetzmann, Ingersoll, and Ivkovic (2000)), non-parametric approaches have been proposed (Kosowski, Timmermann, Wermers, and White (2006)), while another strand of the literature has focussed on portfolio holdings (Daniel, Grinblatt, Titman, and Wermers (1997)). See also Ferson and Khang (2002), Barras, Scaillet, and Wermers (2010), Wermers (2000) and Kapeczyk, Sialm, and Zheng (2005).
44See also Malkiel (1995) and Gruber (1996).
45Timing ability and performance are hardly identifiable at a monthly frequency, except perhaps for a small subset of top performing funds. Recognizing that the observation frequency of returns affects inferences regarding timing and performance, Bollen and Busse (2005) show that performance becomes strikingly more apparent at a higher frequency. Chance and Hemler (2001) and Bollen (2001) further demonstrate that timing ability reveals itself in daily tests but vanishes monthly. Other empirical evidence includes Hendricks, Patel, and Zeckhauser (1993) who describe the "hot-hand" phenomenon in the mutual fund industry and Graham and Harvey (1996) who consider newsletters data.
performance—the alpha generated over a passive benchmark—fails to capture managers’ performance as social interactions intensify. The model points to an alternative measure that is better able to reveal managers’ performance—the dollar value they create.

4.1 Market-Timing

This subsection demonstrates that social interactions weaken managers’ timing ability. In particular, by enhancing price informativeness, social interactions cause timing to be short-lived. If a manager ever had good ideas, sooner or later the market catches up with her. Only managers with highly accurate information can elude this mechanism.

To gauge managers’ timing ability, empiricists run performance regressions on funds’ total returns. These regressions typically augment the CAPM with additional terms that purport to pin down the ability of managers to anticipate future events and to take adequate positions. Admati and Ross (1985), among others, study the relevant performance-regression structure in a theoretical context and list various pitfalls related to such regressions.46 Adopting their approach, my goal here is to determine which additional factor should be added to the CAPM to nail timing in my model.

To make the relevant regression structure apparent, it is convenient to consider the myopic part of managers’ portfolio in (16), which I denote by $\tilde{\theta}_t \equiv \frac{E[dP_t | F_t]}{\gamma \var{dP_t}}$. Adding the hedging part of individual demands does not change the structure, but makes computations less transparent. The return $\tilde{R}_t$ on manager $l$’s myopic portfolio writes

$$d\tilde{R}_t := \tilde{\theta}_t dP_t = \beta_t dP_t^M + \frac{k_t}{\gamma \var{dP_t}} \frac{\sigma_t^2 \lambda_t}{\sigma^2_S + \sigma_t^2} (P_t - \tilde{\Pi}_t - \lambda_2 \Theta_t) dP_t^F$$

where $\beta_t \equiv \frac{\lambda_t}{\gamma \var{dP_t}}$ represents the market price of risk under common perceptions.47

A fund’s returns have three components: the market portfolio, a timing factor measuring the additional performance a manager contributes based on her ideas and a third term that the econometrician treats as noise. Equation (19) contains two key elements. First, the timing factor is proportional to $\frac{\sigma_t^2 \lambda_t}{\sigma^2_S + \sigma_t^2}$, a term that relates to the market learning process. Specifically, as social interactions intensify, market learning

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46See also Dybvig and Ross (1985) and Admati, Bhattacharya, Pfleiderer, and Ross (1986). Recently, Detemple and Rindisbacher (2012) show that a structural approach accounting for the nature of private information yields additional robustness.

47See Appendix F.3.
significantly improves and common uncertainty $\sigma^c$ is greatly reduced. In turn, $\frac{\sigma^c}{\sigma^m + \sigma^c}$ drops and progressively erodes a manager's ability to time the market. Second, the timing factor is quadratic in stock prices $dP$. This indicates that a regression similar to that of Treynor and Mazuy (1966) endogenously arises as a criterion to evaluate timing.

The quadratic aspect of timing originates from managers' informational advantage. To see this, consider excess returns generated by managers $i$ over market returns:

$$d(R^i_t - R^c_t) = \left(\tilde{\theta}_i - \tilde{\theta}_c\right) dP_t = \left(d_{\Delta,t}^i \left( A_{Q,t}^{(2)} - B_{Q,t} \kappa_t \right) - d_{\Theta,t}^i \left( \frac{\lambda_{1,t}^i}{\lambda_{2,t}^i} \right)^2 \right) (\Pi - \hat{\Pi}_t)^2 dt + \ldots$$

Excess returns depend on the square of manager $i$'s informational advantage, $\Pi - \hat{\Pi}^c$. Quadratic prices, present in the timing factor of (16), precisely capture this informational advantage, because the stock price is itself a function of $\Pi - \hat{\Pi}^c$.

Noise traders act randomly. Therefore, they are “sitting ducks” for managers and one should not give credit to a manager for making money on noise traders. For this reason, I do not run the Treynor and Mazuy (1966) regression over manager’s total returns. Instead, I isolate returns $\tilde{R}$ managers solely generate based on fundamental information. From now on, I consider a manager’s informational holdings $\tilde{\theta} \equiv \theta - d_\Theta \Theta$. Informational holdings contain manager’s hedging demand (not only the myopic part), but do not include the fraction they contribute to the supply. Informational holdings are therefore exclusively related to managers’ information. Finally, I run the Treynor and Mazuy (1966) regression over a rolling window, thus causing its coefficients to vary over time as in Ferson and Schadt (1996):

$$\tilde{R}^i_t = \alpha^i_t + \beta^i_t \Delta P_t + \gamma^i_t (\Delta P_t)^2 + \epsilon^i_t, \quad \Delta \leq t \leq T - \Delta. \quad (20)$$

Using (20), I am in a position to evaluate managers’ timing ability by simulating the economy. I focus the analysis on a restricted number of managers. I do so by plotting the results for the average manager in each group. The timing factor $\gamma$ is depicted in Figure 5 and is pooled among managers to ease comparisons across networks. Each column corresponds to a given intensity $\eta$ of social interactions. The market coefficient $\beta$ and the intercept $\alpha$ of (20) are statistically insignificant and are therefore omitted. An insignificant $\alpha$ suggests that the timing factor properly captures managers’ ability.

When the intensity of interpersonal communications is low (Panel A), timing abilities across networks are as one would expect. Managers in Network A (the dotted line) are unable to time the market, while other managers come out as successful market timers.

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48I simulate portfolios for each agent type using the formulae of Appendix F.2. Then, I compute the cross-sectional average using the population dynamics.
Figure 5: Timing Coefficient

Treynor and Mazuy (1966) Regression and Timing. Figure 5 plots the loading on market timing of the regression in (20) over a one-month $\Delta$ rolling window for the average manager in Network A ($\cdots\cdots$), in Network B ($\cdots\cdots$) and managers $i$ (——). Panels A, B and C respectively correspond to an interaction intensity of one meeting twice per year, one meeting every quarter and one meeting every two months. The calibration is reported in Table 1.

For managers in Network B, timing is the strongest. The reason is that informed managers $i$ account for a modest fraction of the population when interactions are moderate. But, for both types of manager, timing ability is long-lived.

As interactions intensify, this result is partly reversed. While managers in Network A and informed managers respectively worsen and improve their timing ability, managers in Network B become progressively unable to time the market—timing vanishes (see Panel B). For an intensity of one meeting every two months ($\eta = 6$ in Panel C), it becomes rapidly impossible to tell managers in Network A and B apart. This result should come as a surprise since social dynamics, by clustering good ideas in Network B, allow managers thereof to longer preserve their informational advantage. But market learning, through the term $\frac{\sigma^{nl}}{\sigma_{S}^{2} + \sigma^{nl}^{2}}$ appearing in (19), progressively impairs their timing ability. That is, social interactions, by improving the market learning process, prevent managers of Network B from keeping their informational advantage, despite good ideas staying local. Only managers $i$ whose views are unaffected by the market remain successful market timers.

4.2 Performance

Social interactions cause timing to be short-lived. I shall now show that social interactions carry similar implications regarding performance. Specifically, social interactions operate on price informativeness to produce non-persistent performance. Additionally, only a small group of funds appear to be top performers, consistent with empirical
findings. The underlying mechanism—word-of-mouth communication—contrasts with alternative explanations, which are either based on the structure of the mutual fund industry (Berk and Green (2004)), on career concerns (Chevalier and Ellison (1999b)) or possibly on market volatility. In particular, unlike Berk and Green (2004) whose mechanism relies on the competitive provision of funds by investors, the mechanism I highlight ignores flows into and out of the fund.

Importantly, my model suggests that alpha becomes a poor measure of performance, as social interactions intensify. Alpha cannot differentiate managers’ level of performance, despite large performance spreads across managers. It only measures the rate at which managers add value. In turn, it fails to reproduce an accurate performance ranking and underestimates performance persistence. I show that the dollar value a manager creates is a better performance criterion. This prediction is in line with recent empirical findings by Berk and van Binsbergen (2012).

It is insightful to first consider the dollar value managers create. In my model, funds do not pay out their income nor their capital gains and, therefore, the dollar value managers generate coincides with the fund’s net asset value (NAV): \( E]\left[ \sum_{t=0}^{\tilde{\theta}} \prod_{d} P_s \right] \). To compute funds’ NAV, I assume that each fund starts with an initial wealth equal to zero and then evaluate how much value is added by each fund on average.\(^{49}\) The average fund’s NAV is plotted in Figure 6 below as a function of time and social interactions \( \eta \).

**Figure 6: Net Asset Value (NAV)**

**NAV and Social Interactions.** Figure 6 plots a fund’s NAV as a function of time for the average manager in Network A (Panel A), in Network B (Panel B) and manager \( i \) (Panel C). Each is plotted for an interaction of one meeting twice per year (\( \cdots \cdots \)), one meeting every quarter (\( \cdots \cdots \)) and one meeting every two months (\( \cdots \cdots \)). Table 1 reports the calibration.

```
<table>
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<th>Interaction</th>
<th>Panel A</th>
<th>Panel B</th>
<th>Panel C</th>
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<td>2 meetings per year</td>
<td>( \cdots \cdots )</td>
<td>( \cdots \cdots )</td>
<td>( \cdots \cdots )</td>
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<td>4 meetings per year</td>
<td>( \cdots \cdots )</td>
<td>( \cdots \cdots )</td>
<td>( \cdots \cdots )</td>
</tr>
<tr>
<td>6 meetings per year</td>
<td>( \cdots \cdots )</td>
<td>( \cdots \cdots )</td>
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</tbody>
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```

Based on a funds’ NAV, managers’ performance is as one should expect. Managers in Network A make some modest profits (on momentum; see below), but end up destroying

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49 In practice, one may recoup a fund’s dollar value by adding back past dividends to the fund’s NAV. A similar exercise is conducted in Bollen and Busse (2005), for instance.
value when the stock pays out (see Panel A). Managers in Network $B$ make significantly more money (see Panel B). Finally, informed managers $i$ sharply come out as top performers (see Panel C).

Three key aspects to Figure 6 need to be emphasized. First, average profits generated by managers in Network $B$ and managers $i$ significantly increase as social interactions intensify. The reason is two-fold: firstly, these managers represent a larger fraction of the population and, secondly, they speculate more aggressively to exploit their informational advantage before the market digests it (see Subsection 6.2). These profits create large spreads in performance across networks. Second, the performance of managers with superior information is persistent. Finally, while managers in Network $B$ may end up partly destroying the value they added when interactions are intense ($\eta = 6$), the ranking of managers is robust no matter how intense social interactions are. Hence, the dollar value added by a manager provides an accurate description of her performance.

But this is just not the way the empirical literature usually evaluates manager’s performance. Empiricists rather choose a passive benchmark, over which abnormal returns added by a manager are computed. The benchmark collects returns on passive strategies, which empiricists deem managers should not be rewarded for. In my model, two passive strategies are relevant to consider: first, as (19) indicates, one should not reward a manager for buying the market portfolio, since this strategy only requires to observe the tape. Second, one should not reward a manager for pursuing a momentum strategy. Here, I anticipate the results of Sections 5 and 6—social interactions produce momentum in stock returns and cause lesser-informed managers to implement momentum strategies; accordingly, I consider a benchmark regression that includes market returns and the (times-series) momentum factor of Moskowitz, Ooi, and Pedersen (2011):

$$\tilde{R}_t = \alpha_t + \beta_t \Delta P_t + \delta_t \text{sign}(\Delta P_{t-\Delta}) \Delta P_t + \epsilon_t, \quad \Delta \leq t \leq T - \Delta. \quad (21)$$

The regression in (21) is essentially the Carhart (1997) risk-factor model without Fama and French (1995) factors (there is only one stock in my model). Most empirical studies use this benchmark. Alpha and the loading $\delta$ on momentum are plotted in Figure 7 below as functions of time and the meeting intensity $\eta$.

As long as social interactions are moderate (Panel A), managers can be accurately ranked based on their alpha. Managers in Network $A$ rapidly destroy value while others create value; their performance is long-lived.

Yet, as social interactions intensify, the picture becomes hazier. Performance in Network $A$ and $B$ converges and managers in Network $B$ do not maintain their performance (Panel B). Performance only persists for a small group of managers
**Benchmark Regression, Alpha and Momentum.** Figure 7 plots alpha and the momentum loading in the benchmark regression in (21) over a one-month \( \Delta \) rolling window for the average manager in Network \( A \), in Network \( B \) and manager \( i \). Each column corresponds to an interaction of one meeting twice per year, one meeting every quarter and one meeting every two months. The calibration is reported in Table 1.

(informed managers \( i \)). And when meetings frequently take place (Panel C), alpha is almost inconclusive as to managers’ ranking. It becomes literally impossible to distinguish managers in Network \( A \) from those in Network \( B \), despite the large spread in profits across the two networks. Consistent with empirical findings, performance is, overall, dramatically non-persistent, expect for a small fraction of the population. Performance ceases to persist *a long time ahead of the announcement date*, which indicates that this phenomenon is solely the result of social interactions.

Alpha fails to capture large spreads in performance. This shortcoming is particularly striking when comparing the performance in Network \( B \) with that of managers \( i \) in Panel C: informed managers \( i \) appear to generate less alpha than managers of Network \( B \), while they actually produce ten times more dollar value. The reason is straightforward—alpha ignores that managers accumulate wealth. Alpha simply cannot differentiate two managers, who respectively generated one million and one billion dollar value. There are two important implications thereof. First, alpha underestimates performance persistence. Alpha becomes rapidly insignificant while managers may still be adding
significant dollar value. Second, alpha is unable to tell managers apart, if the rate at which managers add value frequently changes over time.

I conclude this section with a comment on the implications of momentum for performance (momentum itself is the subject of the next section). Some empirical studies argue that managers’ performance strongly relates to momentum: Grinblatt, Titman, and Wermers (1995) and Wermers (1999) conclude that funds that invest on momentum are more likely to perform. Brown and Goetzmann (1995) report that performance persistence is mostly accounted for by funds that repeatedly lag the S&P500 or a passive benchmark. Finally, Carhart (1997) finds that the “hot hands” phenomenon of Hendricks, Patel, and Zeckhauser (1993) is driven by the one-year momentum effect.

However, in light of my model, these conclusions may have to be reexamined. In the colorful words of Cohen, Coval, and Pastor (2005), “it seems hard to argue that sitting on one’s laurels and doing nothing is a managerial skill that should be given credit”. Panels E and F of Figure 7 show that managers in Network A positively load on momentum, while better-informed managers negatively load on momentum. Hence, lesser-informed managers are momentum traders and better-informed managers are contrarians. Panel A of Figure 6, then, clearly demonstrates that profits made on momentum are significantly lower than those made on fundamental information.

5 Momentum in Stock Returns

In the previous section, I consider momentum as a factor to be added to a benchmark regression, yet not eliciting the reason for its presence; this is the task of this section. Identifying momentum in a theoretical, rational context is fundamental in many respects. First, momentum is one of the most pervasive facts in Financial Economics. Second, well-accepted explanations for momentum are mostly behavioral. In contrast, momentum arises here as a rational phenomenon driven by social interactions, consistent with the empirical finding of Hong, Lim, and Stein (2000). Third, mutual fund managers are likely to play an important role in the momentum mechanism (Wermers (1999)). Moreover, momentum provides managers with an opportunity to make profits. For instance, Avramov and Wermers (2006) find that returns predictability is an essential determinant of managers’ performance. Finally, the statistical properties of stock returns are central, as empiricists use returns to compute conditional expectations of managers’ performance. Doing so, Ferson and Schadt (1996) show that usual measures of managers’ performance are substantially improved.


To understand how social interactions produce momentum, a crucial observation needs to be made. It usually takes very specific assumptions for returns to feature momentum in a noisy rational-expectations equilibrium (REE): i) In the context of Wang (1993), momentum mechanically arises if the supply is extremely persistent. ii) In a REE à la Wang (1993) with a finite horizon, Holden and Subrahmanyam (2002) show that momentum obtains if the mass of informed agents—managers in my model—is sufficiently large. iii) In a REE à la He and Wang (1995), Cespa and Vives (2012) demonstrate that returns exhibit momentum if the average precision across agents shows sufficient improvement over time. While assumptions ii) and iii) are admittedly somewhat ad-hoc, they happen to be endogenous implications of social dynamics in my model. Specifically, social interactions endogenously drive the mass of managers, and the average precision over time, thus addressing ii) and iii). Social interactions therefore generate momentum in stock returns and reaffirm the role of information as a main driver of serial correlation, as I shall now show.

It is first necessary to recall the way prices are formed. The discussion of Subsection 3.1 implies that the price has the form

$$P_t = \int_{j_t \in I} E[\Pi + \delta|\mathcal{F}_t|]d\nu(j_t) + \lambda_{2,t} \Theta_t$$

where the first and the second term respectively represent the contribution of information and risk to prices.52

Two observations regarding (22) are hopefully helpful. First, let social interactions be intense, i.e., $\eta \to \infty$; then, every manager instantaneously becomes informed as soon as $t > 0$ and the price in (22) reduces to $P_t = \Pi + \lambda_{2,t} \Theta_t$—it has no informational content.53 As a result, price variations are solely driven by supply shocks and the serial correlation over a period of length $\Delta$ writes $\text{cov}(\Delta P_{t-\Delta}, \Delta P_t) = (\lambda_{2,t+\Delta} - \lambda_{2,t})/(\lambda_{2,t} - \lambda_{2,t-\Delta})$. Hence, unless the compensation for risk $\lambda_2$ evolves in a pronounced non-monotonic fashion, prices are strongly positively autocorrelated and the sign of the serial correlation is determined by the compensation for risk in an almost mechanical manner.

Second, let the economy be absent of social interactions, i.e., $\eta \to 0$. This case nests the setting of He and Wang (1995), except for allowing trading to be continuous. Serial correlation is computed over a one-month period $\Delta$, as usually done in empirical studies, and is depicted in Panel A of Figure 8 below.54 The contribution of risk (the dotted

52See Appendix E.

53In this case, $\lambda_2$ solves the following system of coupled differential equations: $\lambda_{2,t}' = \gamma \sigma_\delta^2 \lambda_{2,t}^2 + \sigma_\delta^2 \lambda_{2,t} M_{1,t} + a \sigma_\delta \lambda_{2,t}$, $\lambda_{2,T} = -\gamma \sigma_\delta^2$ and $(M_{1,t})' = \sigma_\delta^2 (M_{1,t})^2 - \sigma_\delta^2 \gamma^2 \lambda_{2,t}^2 + 2 a \sigma_\delta M_{1,t}$, $M_{1,t} = \gamma^2 \sigma_\delta^2$.

54See Appendix F.1.
line) is positive, reminiscent of the perfect-information case just discussed, while the contribution of information (the dashed line) is essentially insignificant. In spite of this, returns are weakly negatively autocorrelated (the solid line). This negative correlation is due to the interaction between information and risk into prices (the dashed-dotted line), as average market beliefs and the compensation for risk are inversely related: if the informational content of prices rises ($\lambda_1$ increases), the compensation for risk $|\lambda_2|$ decreases as the result of the weaker information asymmetry. Similar to the case in which social interactions are intense, the informational content of prices does not play a direct role. Consequently, as often happens in a REE (e.g., Wang (1993)), returns exhibit reversal.

Introducing a moderate interactions intensity of one meeting twice per year ($\eta = 2$ in Panel B) leads both risk and information to contribute an equal and positive fraction to returns autocorrelation. Yet, the interaction thereof still dominates and even magnifies stock returns reversal. The economic mechanism previously highlighted bites all the same. As a positive shock in the supply occurs, prices experience a decrease (through the compensation for risk $\lambda_2 < 0$), which generates low current returns. Since social interactions are moderate and the proportion of well-informed managers is low, managers attribute the shock to noise trading and therefore consider it transitory. They hold on to their speculative positions, thereby inducing stock returns to reverse.

Further increasing the meeting intensity allows one to overturn this mechanism—the individual contribution of information and risk eventually overbalances that of their interaction and a first phase of momentum emerges (Panel C). Because social interactions produce an increasing fraction of well-informed agents (point ii) above), managers become increasingly concerned that price changes may be information-driven. Also, the way private information flows—through word-of-mouth communication—induces a steady increase in managers’ average precision over time (point iii) above) and further causes prices to reveal more information. Now, suppose that prices increase. Since managers $l$ start to attribute price changes to a misevaluation of $\Pi$, they tend to buy shares as they probably underestimated $\Pi$. By buying additional shares, managers push prices further up, which eventually leads to stock returns momentum. When social interactions are intense (Panel D), momentum can be as high as 8% monthly. Clearly, momentum follows from the diffusion of information through prices.

This initial phase of momentum does not carry all the way to $T$, though, as apparent from Panels C and D. The negative relation between information and risk is still at play and eventually gives rise to a late phase of reversal, although rather weak. Reversal is due to both the collapse in the informational content of prices (Panel D of Figure 3) and the surge in the compensation for risk resulting from the pending revelation of $\delta$. 

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Serial Correlation in Returns. Figure 8 plots serial correlation (—) in returns over a one-month period $\Delta$ for the cases of no social interaction (Panel A), of a meeting twice per year (Panel B), one meeting every quarter (Panel C) and one meeting every two months (Panel D). Each is decomposed into the contribution of average market expectations (---), of risk (-----) and of the interaction between both (····). Table 1 reports the calibration.  

Both phenomena are consistent with well-known facts—the first phase of momentum corresponds to early returns continuation documented by Jegadeesh and Titman (1993), and the second phase of reversal is in line with the late over-reaction evidence of De Bondt and Thaler (1985).

While the mechanism highlighted here builds on Andrei and Cujean (2011), the idea that social interactions drive momentum is already present in Hong and Stein (1999), yet it relies on a behavioral model. Furthermore, rational explanations for momentum are often based on risk, as in Berk, Green, and Naik (1999) or in Johnson (2002).55 Importantly, I show that momentum is not the sole result of risk, but that it centrally depends on the diffusion of information through private conversations.

55See Vayanos and Woolley (2010) for an alternative mechanism.
6 Momentum and Contrarian Strategies

Mounting evidence suggests that social interactions influence managers’ portfolio decisions. In a survey conducted by Shiller and Pound (1989), 44% of institutional investors recognize that interpersonal communications impact their portfolio choice. Fund managers’ holdings are strongly related to those of managers operating in the same city (Hong, Kubik, and Stein (2005)). Also, managers bias their portfolio towards firms to which they are connected through an educational network (Cohen, Frazzini, and Malloy (2008)). Similar evidence carries over to individual investors.

In my model, interpersonal communications cause lesser-informed managers to follow the trend and better-informed managers to be contrarians. Yet, perhaps surprisingly, even good ideas may not keep managers from eventually aligning with the market consensus, as social interactions intensify. I show that these trading patterns relate to the way managers bet on price convergence towards its fundamental value.

6.1 Aligning with the Market Consensus

Informational holdings—portfolios ignoring managers’ market-making activity—are not observed by the econometrician. Therefore, they need to be conditioned on publicly available information, namely prices. I follow Brennan and Cao (1996) and regress informational portfolio changes $\Delta \tilde{\theta}^l$ on price changes $\Delta P$ over a period of length $\Delta$, i.e.,

$$E[\Delta \tilde{\theta}^l|\Delta P] = \text{cov}(\Delta \tilde{\theta}^l, \Delta P)/\text{var}(\Delta P)\Delta P.$$  

Although holdings are usually available quarterly, I consider a monthly window to remain consistent with previous sections.

The trading measure, $\text{cov}(\Delta \tilde{\theta}^l|\Delta P)$, is plotted in Figure 9 below, as a function of time and social interactions intensity $\eta$. A first observation, and an important result, is that managers of Network A are strong momentum traders. As apparent in Panel A, $\text{cov}(\Delta \tilde{\theta}^A, \Delta P)$ is positive, which implies that managers of Network A tend to buy shares after price increases (and vice-versa). Intuitively, managers of Network A hold few ideas and thus rely more on public information. Because price changes partially reveal better-informed managers’ information, all the more so when social interactions are intense, they tend to intensify their positive-feedback strategy.

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56 In that respect, large cities appear to be particularly suited places for word-of-mouth communication, for it is where leading mutual fund families concentrate. Large cities are further reported by Christoffersen and Sarkissian (2009) to convey knowledge spillovers and to guide learning.

57 Hong, Kubik, and Stein (2004) documents that investors find the market more attractive when more of their peers participate. Brown, Ivkovic, Smith, and Weisbenner (2008) uncover a strong causal relation between an individual’s decision whether to own stocks and the average ownership of her community. See also Shive (2010), Massa and Simonov (2011) show that college-based interactions influence portfolio decisions. Other evidence includes Grinblatt and Keloharju (2001) or Ivkovic and Weisbenner (2005).

58 The derivation is provided in Appendix F.2.
Unlike managers of Network A, informed managers $i$ can perfectly interpret price changes. If managers $i$ observe a price change triggered by noise traders, they know it simply represents an inappropriate move. If managers $i$ observe a price change driven by the market, they know it merely reflects an imperfect adjustment towards the stock’s actual value, part of which, II, managers $i$ know. Hence, one should expect managers $i$ to systematically trade against the market. Panel C shows that $\text{cov}(\Delta \tilde{\theta}^i|\Delta P)$ is negative and managers $i$ indeed come out as contrarian investors—they buy shares after price decreases (and vice-versa). If conversations often take place, they fiercely bet against the market to exploit their information before the market digests it.

**Figure 9: Trading Behavior**

**Trading Behavior and Social Interactions.** Figure 9 plots the contemporaneous correlation of portfolio and price changes over a one-month period $\Delta$ for the average manager in Network A (Panel A), in Network B (Panel B) and manager $i$ (Panel C). Each is plotted as a function of time, for a social interaction of one meeting twice per year (-----), one meeting every quarter (------) and one meeting every two months (---). The calibration is reported in Table 1.

Better-informed managers are contrarians while lesser-informed managers follow the trend. This result is similar to that of Brennan and Cao (1996) who show that it relates to agents’ precision. Yet, an important difference is that, in my model, precision is endogenized through the number of ideas managers hold (see Subsection 3.1). Moreover, for the range of meeting intensities considered, momentum traders represent a vast majority of the population, a result supported by Grinblatt, Titman, and Wermers (1995) who find that 77% of managers in their sample implement momentum strategies.

Contrarian strategies pursued by informed managers are consistent with Coval and Moskowitz (2001), who document a strong inverse relationship between herding activity and geographic proximity, in line with a local informational advantage. Fund managers break away from the herd in their local investments and “free-ride” on others’

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59See also Colla and Mele (2010) and Watanabe (2008).
information by herding on distant investments. Feng and Seasholes (2004) reach similar conclusions regarding individual investors.60

The trading behavior of managers in Network $B$ offers another intriguing result. One should expect managers of Network $B$, who have access to privileged information, to behave at least similarly to informed managers $i$. But Panel B shows that this conjecture may not always be verified. As long as the market is at an early stage of learning, managers of Network $B$ have sufficiently many ideas to behave like contrarians. Nevertheless, if managers entertain more than two meetings per year on average ($\eta > 2$), $\text{cov}(\Delta \hat{\theta}^B | \Delta P)$ switches sign and they eventually align with the market consensus. This result illustrates the relentless impact of social interactions on trading—word-of-mouth communication causes market learning to improve at great speed and even managers with good ideas cannot keep from eventually following the trend. This tendency to rally to the market consensus is consistent with Wermers (1999).

6.2 Betting on Price Convergence

I now provide the mechanism driving momentum and contrarian strategies previously described. These strategies hinge upon the way managers bet on price convergence; this becomes apparent if one rewrites managers’ portfolio in (14) as

$$\theta'_t - \frac{d_{\theta,t} \Theta_t}{\text{Market-Making}} \equiv \tilde{\theta}'_t = \frac{\varphi'_l}{\lambda_{1,t}} E[P_t - E[\Pi + \delta | F_t^i]] \Pi] + \left( \frac{\varphi'_l}{\lambda_{2,t}} d_{\theta,t} \right) \frac{1}{n'_t} \sum_{k=1}^{n'_t} \epsilon'_k (23)$$

where

$$\varphi'_l = \frac{\sigma^2}{\sigma^2 + \phi'_l n'_t \lambda_{1,t} d_{\theta,t}} + \frac{\phi'_l n'_t}{\sigma^2 + \phi'_l n'_t} d_{\Delta,t}.$$ 61

Managers exploit the time series of prices according to their own views. First, managers can compute the price deviation from its fundamental $\Pi + \delta$ as commonly perceived, $P_t - E[\Pi + \delta | F_t^i]$. Second, managers have access to at least one idea and can refine the common estimate of price convergence. Ideally, managers would like to condition price convergence on $\Pi$, thus giving rise to a) in (23). Yet, due to b), this operation is overwhelmed by errors contained in their set of ideas. Even for managers $i$, who are not affected by b), this operation remains imperfect due to noise traders whose orders continuously produce transitory price deviations through c).

60 That informed managers $i$’s strategy weakly relies on public information is consistent with the empirical conclusions of Kacperczyk and Seru (2007).
61 See Appendices F.1 and F.2 for further details.
Ignoring noise perturbations in b) and c), the loading $\varphi^{l}$ in a) determines how a manager bets on price convergence. $\varphi^{l}$ is a weighted average of her speculative $d_{\Delta}$ and her scaled market-making $\lambda_{1}d_{\Theta}$ positions whose weights depend on both her number of ideas $n^{l}$ and common uncertainty $\sigma^{c}$. One therefore needs to investigate which of the two dominates. To do so, I plot managers’ market-making and speculative positions in Figure 10 and a) in Figure 11 below, both as functions of time and meetings intensity $\eta$.

![Figure 10: Optimal Portfolio Strategies](image)

**Portfolio Strategies and Social Interactions.** Figure 10 plots market-making activities $d_{\Theta}$ (Panels A to C) and speculating activities $d_{\Delta}$ (Panels D to F) for the average manager in Network A and Network B and for manager $i$, respectively. Each is plotted as a function of time, for a social interaction of one meeting twice per year (-----), one meeting every quarter (------) and one meeting every two months (----). The calibration is reported in Table 1.

Consider first managers in Network A. As seen in Panel D of Figure 10, they rush to speculate before better-informed managers arrive, and because prices convey significantly more information initially (see Panel D in Figure 3). Increasing the intensity of meetings further exacerbates managers’ trading aggressiveness, as little time is left to speculate. Moreover, Panel A shows that managers of Network A progressively unwind their market-making positions, since there is a higher chance that they end up on the wrong side of the trade (the fraction of well-informed managers rises).

One should therefore expect the first term in $\varphi^{A}$ to dominate. Yet, because managers of Network A have a moderate number of ideas, their loading $\varphi^{A}$ on price convergence
is actually tilted towards $\frac{\lambda_1}{\lambda_2} d^A_{\Theta,t}$. This term is negative due to the compensation for risk $\lambda_2 < 0$ and, as Panel A of Figure 11 reveals, a) is negative—if the market thinks the stock is overpriced (that is, $P_t > E[(\Pi + \delta)|F_t]$), managers of Network A follow the market and go short (and vice-versa). They are trend-chasers, indeed.

Managers $i$ do the opposite. Their loading $\varphi^i$ sharply reduces to their speculative position $d^i$ (Panel F of Figure 10). They speculate fiercely after the informational content of prices has collapsed and, therefore, when it is risky for lesser-informed managers to speculate. Importantly, managers $i$ can tell that market expectations, on average, will not converge to $\Pi$ before the announcement date. Hence, in the meantime, they can make money by betting against the market. If they find out the market thinks the stock is overpriced, they go long by positively loading $\varphi^i > 0$ on a) (and vice-versa), as seen in Panel C of Figure 11. Needless to say, they are contrarians.

**Figure 11: Betting on Price Convergence**

![Figure 11: Betting on Price Convergence](image)

**Price Convergence and Social Interactions.** Figure 11 plots the exposure to price convergence for the average manager in Network A (Panel A), in Network B (Panel B) and manager $i$ (Panel C). Each is plotted as a function of time, for a social interaction of one meeting twice per year (solid), one meeting every quarter (dotted) and one meeting every two months (dashed-dotted). The calibration is reported in Table 1.

Managers in Network B speculate on price convergence in a non-trivial manner. As apparent from Panels B and E of Figure 10, they both intensively speculate and make the market for noise traders, as long as informed managers do not represent a major threat. Therefore, good ideas initially allow managers of Network B to trade alongside managers $i$ ($\varphi^B$ is tilted towards $d^B_{\Theta,t}$). Now, as interactions intensify, market learning shows a substantial improvement and common uncertainty $o'$ is greatly reduced (see Panel C in Figure 3). As a result, their loading $\varphi^B$ shifts towards $\frac{\lambda_1}{\lambda_2} d^B_{\Theta,t}$ and managers of Network B eventually bet along with the market (see the solid and dashed-dotted lines in Panel B of Figure 11). That is to say, *even good ideas cannot keep a manager from aligning with the market consensus.*
While this mechanism may have the flavor of informational cascades (Bikhchandani, Hirshleifer, and Welch (1992)), Bayesian managers do not disregard—but optimally give less and less weight to—their own ideas. They increasingly rely on market information. This mechanism is endogenously conveyed through the informational content of prices.

7 Conclusion

I show that word-of-mouth communication among managers plays an important role in the mutual fund industry. First, social interactions cause managers’ performance not to persist—social interactions lead to greater efficiency and progressively erode managers’ informational advantage. Second, social interactions generate momentum in stock returns. In my model, momentum arises as a rational phenomenon whose underlying mechanism depends on the diffusion of information among managers. Finally, social interactions give rise to trading patterns that are consistent with those identified in the mutual fund industry. Except for a handful of top performers who consistently break away from the herd, momentum trading becomes sooner or later an optimal strategy.

The model offers a new testable prediction—the dollar value added by a manager is a better measure of her performance than the alpha she generates. I show that alpha fails to capture two important aspects of managers’ performance: as social interactions intensify, alpha $i$ underestimates performance persistence and $ii)$ becomes unable to tell managers apart, despite large spreads in trading gains across managers.

This paper suggests many potentially interesting avenues for future research. First, the social dynamics of my model may be adapted for the purpose of studying fads and fashions in the marketplace. Rumors may propagate and drive prices away from their fundamental value. If agents are allowed to act strategically, this may lead to a new theory of price manipulation. Second, the relation between word-of-mouth communication and prices is only one-way—social interactions impact prices, but prices do not impact the way agents interact socially. A challenging extension involves a full-fledged equilibrium in which social interactions and prices feed back both ways. Third, in the “limits to arbitrage” literature, social interactions may mitigate two kinds of risk: word-of-mouth communication may help arbitrageurs to, firstly, synchronize their trades to arbitrage bubbles away and, secondly, reduce convergence risk by accelerating the price adjustment towards its fundamental value. Finally, this paper focuses on managers’ market-timing ability. An economy with multiple stocks is a natural extension of the present work and would allow one to study the effects of social interactions on selectivity. I leave investigations along these lines for future research.
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