

Han, Jungsuk; Sangiorgi, Francesco

Working Paper

Searching for information

Sveriges Riksbank Working Paper Series, No. 300

Provided in Cooperation with:

Central Bank of Sweden, Stockholm

Suggested Citation: Han, Jungsuk; Sangiorgi, Francesco (2015) : Searching for information, Sveriges Riksbank Working Paper Series, No. 300, Sveriges Riksbank, Stockholm

This Version is available at:

<https://hdl.handle.net/10419/129714>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

SVERIGES RIKSBANK
WORKING PAPER SERIES

300



Searching for Information*

Jungsuk Han and Francesco Sangiorgi

May 2015

WORKING PAPERS ARE OBTAINABLE FROM

Sveriges Riksbank • Information Riksbank • SE-103 37 Stockholm

Fax international: +46 8 787 05 26

Telephone international: +46 8 787 01 00

E-mail: info@riksbank.se

The Working Paper series presents reports on matters in the sphere of activities of the Riksbank that are considered to be of interest to a wider public.

The papers are to be regarded as reports on ongoing studies and the authors will be pleased to receive comments.

The views expressed in Working Papers are solely the responsibility of the authors and should not to be interpreted as reflecting the views of the Executive Board of Sveriges Riksbank.

Searching for Information*

Jungsuk Han[†] and Francesco Sangiorgi[‡]
Sveriges Riksbank Working Paper Series

No. 300

May 2015

Abstract

This paper provides a microfounded information acquisition technology based on a simple framework with information search. When searchable information is limited, an agent encounters increasingly more redundant information in his search for new information. Redundancy slows down the learning process and generates decreasing returns. Furthermore, as multiple agents search for information from the same source, limited searchability leads to covariance as the acquired information becomes increasingly more overlapped among agents. Using an asymptotic approach, we construct a tractable mapping from resource (attention) allocations to the precision and the correlation of agents' information under varying degrees of searchability of information. We study two economic applications with endogenous information acquisition using our model: (i) a “beauty contest” coordination game, and (ii) a noisy rational expectations equilibrium.

JEL Classification Codes: C65, D80, D81, D83, G11, G14

Keywords: information processing, concavity, precision, asymptotic analysis, coordination games, portfolio choice, financial equilibrium.

*The views expressed in this paper are solely the responsibility of the author and should not be interpreted as reflecting the views of the Executive Board of Sveriges Riksbank.

[†]Stockholm School of Economics, E-mail: Jungsuk.Han@hhs.se.

[‡]Stockholm School of Economics, E-mail: Francesco.Sangiorgi@hhs.se

1 Introduction

It is a truism that available information for economic decision making is scarce, and acquiring information is costly and subject to frictions. One such friction could be the scarcity of cognitive resources such as limited attentional capacity as pointed out by Kahneman (1973). Alternatively, there can be lack of other types of resources such as time, budget, skills or even social networks that facilitate collecting useful information. In the presence of these frictions, available resources should be allocated optimally in searching and processing information to make a more informed decision. The economic literature often employs a set of assumptions that allows quantifying the amount of collected information given an input of resources. However, there has been a scarcity of theoretical justifications to support such assumptions. Our paper provides a microfoundation for an information acquisition technology in the presence of impediments to information search, and investigates its implications in economic and financial decision making.

Our framework on learning under imperfect information searchability is based on the following simple intuition: As an agent keeps searching for new information, it is likely that he would encounter some overlapping—and therefore redundant—pieces of information from the past searching activities. The tendency of increasing redundancy results in diminishing returns to scale in information search, and such concavity of informativeness is more pronounced when the total amount of potentially observable information (henceforth, “searchable information”) is more limited. Similarly, multiple agents who search in an identical source of information would also face increasing redundancy as more information is collected, thus, their acquired information becomes increasingly more similar. Such commonality of acquired information is more pronounced when searchable information is more limited.

We formalize the aforementioned intuition by employing an urn model with an asymptotic approach. Consider drawing balls with replacement from an urn with a finite number of balls; drawing a ball from an urn with replacement is interpreted as collecting a signal through search. Because the collected balls are replaced into the urn, the odds of drawing a previously-collected ball increases each time an agent draws a ball from the urn. In the context of information acquisition, drawing a previously-collected ball means collecting a redundant (thus uninformative) signal. Because each new signal becomes increasingly less informative on average due to redundancy, the expected overall informativeness is concave in the number of collected signals.

Such concavity is more pronounced as searchable information is more limited (or the urn is smaller). Therefore, the expected precision of acquired information becomes concave in the input of resources. However, one may find it rather difficult to apply such a result to most of economic applications because the resulting precision is random and discrete given the input of resources. Considering the limiting case in which each signal becomes infinitesimally small, we can study the continuous limit of a precision function under which the law of large numbers can be applied. This asymptotic approach allows us to obtain a smooth and deterministic function maps the inputs of resources used into the precision of the information that is eventually collected by an agent (see Theorem 2.1). The curvature of this asymptotic precision function decreases with the amount of searchable information, thus a smaller curvature is associated with a higher efficiency of information search.

We also formalize the case with multiple agents using the same logic; imagine that they are independently drawing balls from a single urn which is interpreted as a shared source of information. Because the number of balls in the urn is finite, they tend to gather a more similar set of balls as they increase the number of drawings from the urn. Furthermore, such tendency is more pronounced as the number of balls in the urn becomes smaller. In the context of information acquisition, the shared component of agents' collected signals grows larger as more information is acquired by each agent. Consequently, the correlation of their acquired information increases in the degree of information acquisition, and such tendency is more pronounced when information searchability is lower (Theorem 2.2). This information acquisition technology developed in our paper provides a framework of endogenizing the “publicity” of the acquired information; the correlation between different agents' information is endogenously determined in terms of the input of resources by each agent as well as searchability of information from the source. In the limit case where the number of agents is large, the noise in each agent's acquired information can be decomposed into a public component and an idiosyncratic component where all the components are independent of each other (Corollary 2.1). This framework provides a microfoundation for popular setups in the literature such as private signals with imperfect correlations among agents and private signals with both a public and a private component of noise.

We study two applications of our information acquisition technology. In the first application, we study a “beauty contest” coordination game with endogenous information acquisition.

Our setup follows a standard two-period setup in the literature: Agents' final payoffs depend on the quadratic distance of actions from an unobserved fundamental value and the average action. To acquire information prior to taking the actions, agents can allocate their efforts (or resources) among different information sources to maximize their ex-ante utility. In the recent debate in the related literature, there are mixed messages about the determinacy (or the possibility of multiple equilibria) for coordination games with endogenous information acquisition. Hellwig and Veldkamp (2009) find that the endogenous choice of how much public information to acquire naturally leads to multiple equilibria. In contrast, Myatt and Wallace (2012) assume an information structure similar to the representation that we obtain in Corollary 2.1 and find a unique equilibrium. The results of our analysis lie somewhere in between these two papers. In our setup, the endogenous publicity of the information that is acquired by the agents is not enough to guarantee a unique equilibrium unless the coordination motive is sufficiently weak. When the mapping from agents' effort choices to information is endogenously derived as in our paper, we show how non-concavities arise that can lead to multiple equilibria. Hence, the microfoundation provided in our paper is relevant because it leads to qualitatively different implications. These implications shed new light on the relation between the information structure and equilibrium determinacy in coordination games with endogenous information.

We then specialize to a setup with only two information sources. One of them is superior to the other in the sense that it offers more precise information about the fundamental given the same level of inputs. On the other hand, because of its lower searchability, the inferior source provides information that is more correlated among agents. Therefore, if other agents are leaning from this source, it gives more precise information on what the other agents will do. When the coordination motive is sufficiently strong, there exists an equilibrium in which all agents choose to focus on the inferior information source. Because less searchable information leads to more covariance, this equilibrium outcome becomes more "likely" (i.e., it exists on a larger set of parameters) precisely when the inferior information source becomes more inefficient. This outcome may not be socially optimal because agents are acting based on information from a less efficient source. For instance, the inferior information equilibrium is associated with an average action that is more volatile and less correlated with the fundamental. Our results can be applied to situations with strategic complementarity such as bank runs, analysts' herding behavior, etc. For example, agents may decide to run on a healthy bank based on less accurate

information (e.g., rumors) instead of investigating into more accurate sources of information because information from a less accurate source is more likely to be correlated due to imperfect information searchability.

Our second application is in the context of portfolio optimization and financial equilibrium. We begin by solving the problem of an investor who allocates his resources to acquire information on risky assets prior to choosing his portfolio. In a partial equilibrium setup with exogenous prices, the investor tends to concentrate his resources on the assets with more information searchability, thereby neglecting other assets. Under-diversification arises naturally as the investor concentrates his portfolio on a few assets that allow him to exploit private information best. Furthermore, our results relate the lack of portfolio diversification to the investors' availability of resources for information search and are therefore consistent with the empirical findings that retail investors generally hold highly-concentrated portfolios.

To understand the pricing implications of these forces, we then embed this problem in a noisy rational expectations equilibrium. In equilibrium, an increase in searchability of information in one asset always improves liquidity and informational efficiency for this asset. However, its effect on the other assets crucially depends on the strength of the externality of information revelation through prices. This is because more searchable information is reflected faster in asset prices, thereby reducing investors' incentives to gather costly information on such assets. Hence, the strength of this information externality determines whether the investors allocate more or less resources to the other assets and therefore determines the sign of the "informational spillovers" onto the other assets. If the information externality is strong (because, for instance, investors devote significant resources to information search and prices are very informative), then an increase in information searchability in one asset leads to more information acquisition in the other assets. In turn, this has a positive effect on the liquidity and the informational efficiency of the other assets—a positive informational spillover. If the information externality is weak, then the partial equilibrium force dominates and results in an information crowding out effect. In turn, this effect results in lower liquidity and informational efficiency for the other assets. These results point to cross market linkages that arise due to investors' information choices and may shed light on how different price behaviors (such as price delay to information) may arise due to different analysts' coverage in case of small firms.¹

¹See, for example, Hou and Moskowitz (2005) to review related empirical findings.

In the literature, there have been various formulations that quantify the amount of collected (or processed) information. One of well-known attempt is rational inattention theory based on entropy theory. In his seminal paper, Sims (2003) connected information theory to agents' utility maximization problem using entropy as the measure of information. Due to its practical usefulness, there have been numerous applications in economics and finance based on such rational inattention framework.² For example, Peng (2005) shows a financial equilibrium with information capacity constraints. While the entropy is a convenient and useful measure of information, it may not reflect relevant features of learning problems such as impediments to information search in our model. As was pointed by Marschak (1974), entropy is only relevant to the cost of communicating rather than the cost of searching and collecting information. The original idea of Shannon (1948) is not meant for information processing in economic contexts. In that context, the entropy measure is suitable as communicating constraint rather than information acquisition constraint. Shannon's second proposition asserts that we can transfer a signal without errors under certain capacity limit by using an optimal coding scheme. This optimal coding scheme may not apply to natural languages or economic and financial terms. Developments in information technology imply that we bear minimum costs of communicating; however, natural language is far from being an optimal coding scheme. More importantly, entropy is silent about searching and collecting information. In contrast, our model provides a microfoundation for measuring information in an environment where information search is important. Our results complement the existing literature (such as those in rational attention), and contribute to it by finding further implications that arise from impediments to information search.

The organization of the paper is as follows. Section 2 develops the framework of information acquisition under imperfect information searchability. Section 3 studies a coordination game with complementarities as an example of possible applications. Section 4 studies a portfolio optimization problem as an example of possible applications. Section 5 concludes.

²See, for example, Veldkamp (2011) for an excellent survey on applications in macroeconomics and finance.

2 Information Search

In this section, we develop our methodology and characterize endogenous information under imperfect information searchability. We begin by describing the basic setup, then derive the asymptotic precision function (Theorem 2.1) and the asymptotic covariance function (Theorem 2.2). Then we derive our main result—the joint distribution of agents’ information after information search (Theorem 2.3). Finally, we provide a public-private decomposition of the resulting information structure (Corollary 2.1).

2.1 The Setup

2.1.1 Basic signals

Consider an economic agent who is endowed with limited information processing resources (henceforth, resources) that allow the agent to search necessary information. The agent acquires information using his resources in order to resolve uncertainties that are relevant to his payoffs. There is a random variable of interest, θ , which follows a normal distribution with mean $\bar{\theta}$ and variance τ_θ^{-1} . For example, θ could be the payoff of an investment opportunity such as the liquidation value of a tradable asset. Suppose the underlying source of information on θ is given by a set \mathbf{L} of basic signals that consists of $L \in \mathbb{N}$ distinct signals on θ . Each basic signal $m \in \{1, 2, \dots, L\}$ in \mathbf{L} is given by

$$s^m = \theta + \epsilon^m, \tag{1}$$

where $\epsilon^m \sim i.i.d. \mathcal{N}(0, \tau_\epsilon^{-1})$ is a noise that is independent of θ . We refer to τ_ϵ as the precision of the basic signal s^m .

2.1.2 Information searchability

We define information search as a process of gathering information by using endowed resources. We say that information search is easier (or harder) if the same input of resources resolves a greater (or smaller) amount of uncertainty about the variable of interest. Therefore, “information searchability” is defined as the degree of resolution of uncertainty with respect to the increase in resource input. Assuming that a fixed amount of resource input gives the agent a

signal in Eq. (1), information searchability is inversely related to the possibility of encountering redundant signals in his search process.

We formalize the idea of information searchability using an urn model. Consider the set of signals \mathbf{L} to be an urn, and the basic signals to be balls in the urn. Imagine that the agent is sequentially drawing a ball with replacement from the urn. The agent can identify the index of each signal, thus he knows whether a signal is redundant or not given the set of collected signals. If the number of balls in the urn is limited, the chance of drawing a ball that is distinct from the balls drawn in the previous trials would get smaller as the agent draws more balls from the urn.

The following assumption embeds this idea of impediments to information search by allowing redundancy among acquired signals.

Assumption 2.1. *Signals are drawn with replacement from \mathbf{L} .*

This assumption plays a critical role in our model because it gives a foundation for the concept of information searchability. The opposite case to this assumption is sampling without replacement, in which case acquired signals are never redundant. In this case, any increases in the input of resources would be directly translated into a greater amount of information (or a greater resolution of uncertainty) regardless of the scale of resource investment. On the other hand, the assumption of sampling with replacement in Assumption 2.1 makes it impossible to maintain the constant returns to scale in information search.

2.1.3 Precision function

Because redundant signals are completely uninformative, the informativeness of a set of acquired signals only depends on the distinct signals among them. Let H denote the set of distinct signals among those acquired by the agent, and let h denote the number of signals in H . Let $S(h)$ denote the mean of the signals s^1, s^2, \dots, s^h in H as follows:

$$S(h) = \frac{1}{h} \sum_{m \in H} s^m = \theta + \frac{1}{h} \sum_{m \in H} \epsilon^m. \quad (2)$$

Notice that $S(h)$ is a sufficient statistic for the signals acquired by the agent. By the standard Bayesian belief update formula, the precision of the posterior belief about θ conditional on

observing the signal $S(h)$ is given by

$$\text{Var}[\theta|S(h)]^{-1} = \underbrace{\tau_\theta}_{\text{precision of prior belief}} + \underbrace{\tau_\epsilon h}_{\text{signal precision}}. \quad (3)$$

That is, the set of h i.i.d. signals is equivalent to having a single signal with precision that is h -times higher than that of each individual signal in the set. These observations lead to the following definition of the precision function given the number of distinct signals that are collected:

Definition 2.1. *The precision function $\Phi : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ is defined by*

$$\Phi(h) = \tau_\epsilon h, \quad (4)$$

where h is the number of distinct basic signals drawn from \mathbf{L} , and τ_ϵ is the precision of each basic signal.

Suppose that l signals are drawn with replacement from a finite set \mathbf{L} which consists of L distinct signals. We let \tilde{h} denote the (random) number of distinct signals among l collected signals. The following lemma derives the expected number of distinct signals $E[\tilde{h}]$.

Lemma 2.1. *Suppose that signals are drawn l times from a set of L distinct signals. Then, the expected number of distinct signals among the collected signals is given by*

$$E[\tilde{h}] = L \left[1 - \left(1 - \frac{1}{L} \right)^l \right]. \quad (5)$$

Proof. A more general proof for this can be found in Stadjé (1990). For each $m \in \{1, 2, \dots, L\}$, we define \tilde{h}^m to be one if signal s^m is collected eventually, and zero otherwise. Then, it is immediate that $\text{Pr}(\tilde{h}^m = 1) = 1 - \left(\frac{L-1}{L}\right)^l$. Because $\tilde{h} = \sum_{m=1}^L \tilde{h}^m$, we get

$$E[\tilde{h}] = \sum_{m=1}^L \left[1 - \left(\frac{L-1}{L} \right)^l \right] = L \left[1 - \left(1 - \frac{1}{L} \right)^l \right]. \quad (6)$$

□

Notice that $E[\tilde{h}]$ is monotone increasing and concave in l .³ That is, by drawing more signals from the urn, the expected number of distinct signals increases, but it does at a decreasing rate as more and more signals are being collected. Furthermore, $E[\tilde{h}]$ is monotone increasing in L . Intuitively, the more independent signals are in the urn, the higher the expected number of distinct signals for a given number of draws. Hence, the number of signals in \mathbf{L} reflects the easiness of searching information (or the degree of searchability). We explore these ideas in the next subsection by connecting the precision function with the amount of resources spent on information collection.

2.1.4 Resources and precision

In this subsection, we introduce a set of assumptions that allow us to study an asymptotic limit of precision function. To exploit the law of large numbers, we consider the case where the signals (or balls) in the urn become infinitesimally small so that the number of signals grows to infinity. That is, information acquisition becomes continuous in the limit rather than discrete. This continuous limit yields a smooth and deterministic precision function with desirable properties that can be applied to various economic applications with ease.

To acquire necessary information, the agent needs to use his endowed resources. Let $c \in (0, \infty)$ be the unit of resources required to collect one signal on θ (i.e., the cost of one draw from the urn). We assume that any smaller amount of resources which is less than c cannot be utilized to acquire a signal. Hence, an input of k units of resources would enable the agent to collect $\lfloor \frac{k}{c} \rfloor$ signals.⁴

If an agent could observe all signals in \mathbf{L} , the agent's posterior precision in (3) would be $\tau^* \equiv \tau_\theta + \tau_\epsilon L$. Therefore, τ^* is the upper bound to an agent's information precision, which is regarded as an exogenous feature of the underlying informational environment. As we elaborate below, we will consider the behavior of the precision function as the cost c becomes small while leaving τ^* unchanged. Accordingly, in the next two assumptions we relate the number and

³The monotonicity and concavity can be easily verified from the following:

$$\frac{\partial E[\tilde{h}]}{\partial l} = -L \left(1 - \frac{1}{L}\right)^l \log \left(1 - \frac{1}{L}\right) > 0, \quad \text{and} \quad \frac{\partial^2 E[\tilde{h}]}{\partial l^2} = -L \left(1 - \frac{1}{L}\right)^l \left[\log \left(1 - \frac{1}{L}\right)\right]^2 < 0. \quad (7)$$

⁴ $\lfloor x \rfloor = \max\{z \in \mathbb{Z} | z \leq x\}$.

precision of basic signals to the cost c .⁵

Assumption 2.2. For some $\mathcal{L} \in [0, \infty]$, the number of basic signals in \mathbf{L} is given by $L = \lfloor \frac{\mathcal{L}}{c} \rfloor$.

Because \mathcal{L} determines the number of signals in \mathbf{L} , \mathcal{L} parameterizes the degree of information searchability. All the collected signals will be distinct (thus informative) in the absence of impediments to information search (or in case of perfect searchability, i.e., $\mathcal{L} = \infty$). On the other hand, some of the collected signals may be redundant in the presence of impediments to information search (or in case of imperfect searchability, i.e., $\mathcal{L} < \infty$), thus the number of distinct signals can be strictly lower than the number of collected signals.

Assumption 2.3. For some $\tau \in [0, \infty)$, the precision of each basic signal $s^m \in \mathbf{L}$ equals $\tau_\epsilon = \tau c$.

Therefore, the parameter τ captures the efficiency of each basic signal per unit of cost. For given values of \mathcal{L} and τ , Assumption 2.2 and Assumption 2.3 imply that the total amount of information available to the agent is in fact independent of c . For example, when the required input of resources for one signal decreases by half, the number of basic signals available in the population increases by twice but the precision of each basic signal decreases by half.

We define $\tilde{h}(k; c)$ to be the number of distinct signals drawn from \mathbf{L} given an input of k units of resources when the minimum fraction of resource inputs is set to be c . Then, the precision function according to Definition 2.1 under Assumption 2.3 is given by

$$\Phi(\tilde{h}(k; c)) = \tau c \tilde{h}(k; c). \quad (8)$$

There are two major problems in using the precision function in Eq. (8): First, the precision of information given an input of k units of resources is random because the number of distinct signals is random. Second, the function is not smooth in k because the number of distinct signals is given by discrete numbers. These shortcomings make the precision function defined in Eq. (8) unattractive in most economic applications. To resolve these shortcomings, we will consider the limiting case in which the cost c tends to zero and rely on the following notion:

⁵This following is a technical assumption which obtains smooth extrapolation of discrete choices. Moscarini and Smith (2001) provides a similar extrapolation out of number of sampling.

Definition 2.2. *The asymptotic precision function $\phi : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ is defined to be a function that satisfies the following⁶*

$$\Phi(\tilde{h}(k; c)) \rightarrow \phi(k) \text{ a.s. as } c \rightarrow 0. \quad (9)$$

As we will demonstrate below, the asymptotic precision function $\phi(k)$ in Eq. (9) resolves both problems in Eq. (8). That is, it becomes deterministic and smooth (i.e., continuous in k and also infinitely differentiable with respect to k).

2.2 Asymptotic Precision Functions

Here we derive our main result, the asymptotic precision function in the presence of impediments to information search.

As a benchmark, consider the case of perfect searchability in which signals are drawn from \mathbf{L} *without* replacement. Since there cannot be redundant signals in this case, the number of distinct signals drawn from \mathbf{L} given an input of resources k such that $\lfloor \frac{k}{c} \rfloor \leq L$ is trivially equal to the number of collected signals, $\lfloor \frac{k}{c} \rfloor$. Hence, the corresponding precision function is given by

$$\Phi(\tilde{h}(k; c)) = \tau c \lfloor \frac{k}{c} \rfloor = \tau \lceil k - g(c) \rceil, \quad (10)$$

where $g(c) \leq c$. By taking the limit as c goes to zero, it is immediate to obtain the asymptotic precision in case of perfect information searchability:

$$\phi(k) = \tau k. \quad (11)$$

Now, we turn to the case of imperfect information searchability, i.e., signals are drawn from \mathbf{L} with replacement and $\mathcal{L} < \infty$. Using Lemma 2.1, we can derive the expected number of distinct signals given the resource input k as follows:

$$E[\tilde{h}(k; c)] = \lfloor \frac{\mathcal{L}}{c} \rfloor \left(1 - \left(1 - \frac{1}{\lfloor \frac{\mathcal{L}}{c} \rfloor} \right)^{\lfloor \frac{k}{c} \rfloor} \right). \quad (12)$$

⁶One may alternatively state that $Pr \left[\lim_{c \rightarrow 0} |\Phi(\tilde{h}(k; c)) - \phi(k)| < \alpha \right] = 1$ for each $\alpha > 0$.

Multiplying by c and taking the limit as c goes to zero in Eq. (12) yields

$$E[\tilde{c}\tilde{h}(k; c)] \rightarrow \mathcal{L} \left(1 - \exp \left(-\frac{k}{\mathcal{L}} \right) \right), \text{ as } c \rightarrow 0. \quad (13)$$

Therefore, the expectation of the precision function $\Phi(\tilde{h}(k; c))$ becomes smooth in the limit where c approaches zero. However, it is not clear that the precision function itself will be a deterministic function: proving this result is a non-trivial task because the number of collected signals grows large as c approaches zero but so does the number of redundant signals. Intuitively, proving that uncertainty in $\tilde{c}\tilde{h}(k; c)$ disappears as c approaches zero requires showing that the fraction of redundant signals converges to its expectation, or, more formally, that $\tilde{c}\tilde{h}(k; c)$ can only deviate from $E[\tilde{c}\tilde{h}(k; c)]$ in measure zero cases as c approaches zero. This result is provided the following lemma:

Lemma 2.2. *As $c \rightarrow 0$, the difference between $\tilde{c}\tilde{h}(k; c)$ and $E[\tilde{c}\tilde{h}(k; c)]$ converges to zero almost surely.*

Proof. See Appendix A. □

Because $\Phi(\tilde{h}(k; c)) = \tau \tilde{c}\tilde{h}(k; c)$, Lemma 2.2 gives the main argument in the proof of the following theorem.

Theorem 2.1. *In case of imperfect information searchability, the asymptotic precision is given by*

$$\phi(k) = \tau \mathcal{L} \left(1 - \exp \left(-\frac{k}{\mathcal{L}} \right) \right) \quad (14)$$

As mentioned above, the asymptotic precision function $\phi(k)$ overcomes the two major difficulties that exist in case of $\Phi(\tilde{h}(k; c))$. First, $\phi(k)$ is a deterministic function in k . Second, $\phi(k)$ is a smooth function in k , i.e., $\phi(k)$ is continuous in k and is also infinitely differentiable with respect to k . Furthermore, it has the following standard properties that are frequently assumed in the information economics literature:

- (i) Non-negativity: $\phi \geq 0$,
- (ii) Monotonicity: $\partial\phi/\partial k \geq 0$,

- (iii) Concavity: $\partial^2 \phi / \partial k^2 \leq 0$,
- (iv) Curvature: $-\frac{\partial^2 \phi / \partial k^2}{\partial \phi / \partial k} = 1/\mathcal{L}$.

The precision increases with more input of resources, but the marginal benefits diminish in scale. Furthermore, such diminishing marginal benefits are larger with worse information searchability. These properties fit intuition quite well. As one learns more about one subject, the probability of encountering redundant materials is going up. He realizes that the collected materials are overlapping with those that are previously acquired only after searching. The concavity of the signal precision function is also associated with negatively accelerated learning curve which has been repeatedly reported in cognitive science and psychology. A large body of literature with empirical and experimental evidence finds learning data showing a rapid improvement followed by lesser improvements are best fitted with an exponential function.⁷

The increasing curvature inverse to \mathcal{L} implies that worse information searchability would make the asymptotic precision function more concave. On the other hand, as information searchability improves (i.e., $\mathcal{L} \rightarrow \infty$), the asymptotic precision function (14) converges to the linear function in (11) that is obtained when signals are drawn without replacement. This result is intuitive: as information searchability deteriorates, so does the possibility of drawing redundant signals. We remark that (14) implies $\phi'(0) = \tau$, that is, the precision obtained from the first unit of input only depends on the precision of the underlying information and is unaffected by information searchability—the very first unit of information cannot be redundant, regardless of \mathcal{L} .

In applications, it is common to specify the information acquisition technology in terms of a cost function $k : \phi \mapsto k(\phi)$ that specifies the amount of resources k that are required to collect information with precision ϕ . In our setup, the asymptotic cost function is readily obtained as the inverse of the precision function in (14), $k(\cdot) = \phi^{-1}(\cdot)$, as

$$k(\phi) = -\mathcal{L} \log \left(1 - \frac{\phi}{\tau \mathcal{L}} \right). \quad (15)$$

The cost function $k(\phi)$ has the following properties: it is non-negative, monotone decreasing and concave, with curvature decreasing in the information searchability parameter, \mathcal{L} . Note

⁷See Ritter and Schooler (2001) for surveys on “power law” of learning curve which has been widely observed in cognitive psychology.

that $k(\phi)$ becomes infinite as ϕ approaches $\tau\mathcal{L}$, which represents the upper bound to the information precision. Finally, we remark that $k'(0) = \tau^{-1}$. Differently from what is often assumed in applications, the marginal cost of the first unit of information is bounded away from zero.

Figure 1 provides a graphical illustration of $\phi(k)$ and $k(\phi)$ for different values of the information searchability parameter \mathcal{L} . The functions are linear in the case of perfect searchability ($\mathcal{L} = \infty$) while the curvature decreases for larger values of \mathcal{L} , the precision function becoming less concave and the cost function becoming less convex.

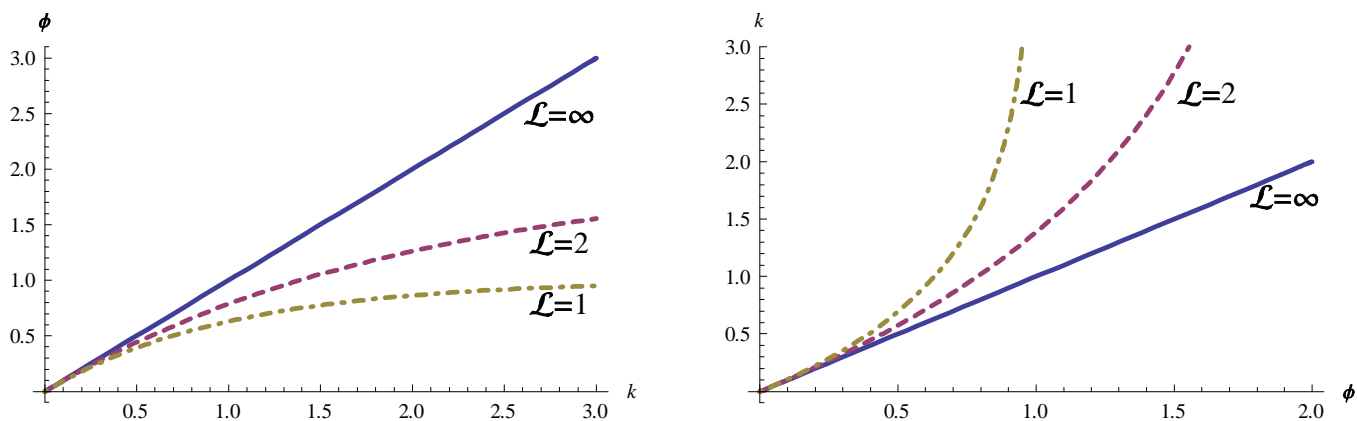


FIGURE 1. Left panel: precision function $\phi(k)$. Right panel: cost function $k(\phi)$. Parameter values: $\tau = 1$ and $\mathcal{L} \in \{1, 2, \infty\}$.

Finally, we call an information source “superior” to the other source only if it provides more precise information than the other source given the same level of inputs. We give a more formal definition of superiority as follows:

Definition 2.3. *Information source i is superior to information source j if i is both more efficient and more searchable, i.e., $\tau^i \geq \tau^j$ and $\mathcal{L}^i \geq \mathcal{L}^j$ with at least one equality being strict.*

A superior information source will always have higher precision given the same level of inputs, i.e., suppose that i is superior to j , then $\phi^i(k) > \phi^j(k)$ for all $k > 0$. One may imagine

that a superior source is always preferred to an inferior source, but later in the paper (Section 3) we show that is is not necessarily the case when agents' actions are strategic complements. This result builds on the multiple agent framework that we develop next.

2.3 Multiple Agents

In this section, we extend our framework to the case of multiple agents. In particular, we focus on the covariance of the acquired signals at the given level of information searchability. The same intuition about drawing balls with replacement from an urn still applies to the case with multiple agents; when the number of balls in the urn gets smaller, the possibility of collecting overlapping information among different agents becomes higher. That is, more severe impediments to information search would induce higher covariance of errors among the acquired signals across different agents.

Suppose that there are I agents in the economy, and let \mathbf{I} denote the set of agents. Adapting the notation introduced in Section 2.1.3, let H_i denote the set of distinct signals acquired by agent i , and h_i denote the number of signals in H_i . Let $S_i(h_i)$ be the mean of the distinct signals acquired by agent i . Then, $S_i(h_i)$ and $S_j(h_j)$ are sufficient statistics for the information acquired by agent i and j :

$$S_i(h_i) = \frac{1}{h_i} \sum_{m \in H_i} s^m = \theta + \frac{1}{h_i} \sum_{m \in H_i} \epsilon^m, \quad (16)$$

$$S_j(h_j) = \frac{1}{h_j} \sum_{m \in H_j} s^m = \theta + \frac{1}{h_j} \sum_{m \in H_j} \epsilon^m. \quad (17)$$

Therefore, the covariance between $S_i(h_i)$ and $S_j(h_j)$ is given by

$$Cov(S_i(h_i), S_j(h_j)) = \frac{1}{\tau\theta} + Cov\left(\frac{1}{h_i} \sum_{m \in H_i} \epsilon^m, \frac{1}{h_j} \sum_{n \in H_j} \epsilon^n\right). \quad (18)$$

Let $H_{i,j}$ denote the set of indices of signals that belong to both H_i and H_j . Then, it is immediate that

$$Cov\left(\frac{1}{h_i} \sum_{m \in H_i} \epsilon^m, \frac{1}{h_j} \sum_{n \in H_j} \epsilon^n\right) = \frac{1}{h_i h_j} Var\left(\sum_{m \in H_{i,j}} \epsilon^m\right) = \frac{h_{i,j}}{\tau c h_i h_j}, \quad (19)$$

where $h_{i,j}$ denotes the number of distinct signals in $H_{i,j}$.

Suppose that agent i and j use an amount of resource k_i and k_j , respectively, when the cost of each signal is set to be c . Denote with $\tilde{h}_i(k_i; c)$ and $\tilde{h}_j(k_j; c)$ the resulting number of distinct signals collected by agent i and j and let $\tilde{h}_{i,j}(k_i, k_j; c)$ denote the number of distinct signals among the commonly collected signals. Of course, for any positive value of c , $\tilde{h}_i(k_i; c)$, $\tilde{h}_j(k_j; c)$ and $\tilde{h}_{i,j}(k_i, k_j; c)$ are random, and so is the covariance among the error terms in the signals $S_i(\tilde{h}_i(k_i; c))$ and $S_j(\tilde{h}_j(k_j; c))$ (see Eq. 19). To restore tractability, we will again consider the limit in which c goes to zero and rely on the following definition:

Definition 2.4. *The asymptotic covariance σ_{ij} of the error terms in the signals $S_i(\tilde{h}_i(k_i; c))$ and $S_j(\tilde{h}_j(k_j; c))$ satisfies*

$$\frac{\tilde{h}_{i,j}(k_i, k_j; c)}{\tau c \tilde{h}_i(k_i; c) \tilde{h}_j(k_j; c)} \rightarrow \sigma_{ij} \text{ a.s. as } c \rightarrow 0. \quad (20)$$

Using an argument similar to Lemma 2.2, we can show that randomness in $c\tilde{h}_{i,j}(k_i, k_j; c)$ disappears in the limit in which the cost c tends to zero. We have:

Lemma 2.3. *As $c \rightarrow 0$, $c\tilde{h}_{i,j}(k_i, k_j; c)$ converges to a deterministic function in k_i and k_j almost surely, i.e.,*

$$c\tilde{h}_{i,j}(k_i, k_j; c) \rightarrow \mathcal{L} \left(1 - \exp \left(-\frac{k_i}{\mathcal{L}} \right) \right) \left(1 - \exp \left(-\frac{k_j}{\mathcal{L}} \right) \right) \text{ a.s., as } c \rightarrow 0. \quad (21)$$

Proof. See Appendix A. □

Then, Lemma 2.2 and Lemma 2.3 together with Eq. (19) provide the proof for the following theorem:

Theorem 2.2. *For each agent pair $i, j \in \mathbf{I}$, the asymptotic covariance of the error terms in the signals $S_i(\tilde{h}_i(k_i; c))$ and $S_j(\tilde{h}_j(k_j; c))$ satisfies*

$$\sigma_{ij} = \frac{1}{\tau \mathcal{L}}. \quad (22)$$

Notice that the asymptotic covariance σ_{ij} is constant and monotone decreasing in $\tau \mathcal{L}$. The latter result confirms our initial intuition that worse information searchability would increase the covariance of acquired information across different agents.

Finally, using Theorem 2.1 and Theorem 2.2, we can obtain the asymptotic correlation of the error terms between the two signals given the input of resources k_i and k_j as follows:

$$\rho(k_i, k_j) = \lim_{c \rightarrow 0} \text{Corr} \left(\frac{1}{h_i} \sum_{m \in H_i} \epsilon^m, \frac{1}{h_j} \sum_{m \in H_j} \epsilon^m \right) = \left[\left(1 - \exp \left(-\frac{k_i}{\mathcal{L}} \right) \right) \left(1 - \exp \left(-\frac{k_j}{\mathcal{L}} \right) \right) \right]^{\frac{1}{2}}. \quad (23)$$

2.4 Asymptotic Normality

While Theorem 2.1 and Theorem 2.2 show the second moments of the error terms in the asymptotic signals, the proof of the next theorem derives their joint asymptotic distribution. We can summarize our results as follows:

Theorem 2.3. *For each agent pair $i, j \in \mathbf{I}$ using input k_i and k_j , respectively, as c goes to zero the information acquired by agent $i, j \in \mathbf{I}$ is equivalent to the asymptotic signals*

$$S_i(k_i) = \theta + \epsilon_i, \quad (24)$$

$$S_j(k_j) = \theta + \epsilon_j, \quad (25)$$

where ϵ_i and ϵ_j are jointly normally distributed with mean zero and variance-covariance matrix $\Sigma_{i,j}$, where

$$\Sigma_{i,j} = \begin{pmatrix} \phi(k_i)^{-1} & \frac{1}{\tau \mathcal{L}} \\ \frac{1}{\tau \mathcal{L}} & \phi(k_j)^{-1} \end{pmatrix},$$

where the function $\phi(\cdot)$ is as in Eq. (14).

Proof. See Appendix A. □

It is worth mentioning that Theorem 2.3 is proved in the appendix without imposing any distributional assumption about θ or ϵ . Therefore, our results in the theorem can be generalized to broader classes of distributions than the normal distribution.

2.5 A public-private decomposition of signals' noise terms

From Theorem 2.3, we can represent each asymptotic signal $S_i(k_i)$ by decomposing the noise term ϵ_i into two parts as follows:

$$S_i(k_i) = \theta + \mu + \eta_i, \quad (26)$$

where μ is a common component of noise, and η_i is an idiosyncratic component of noise such that

$$\mu = \frac{1}{I} \sum_{i=1}^I \epsilon_i, \quad \eta_i = \epsilon_i - \mu. \quad (27)$$

The next corollary provides a characterization of the representation in Eq. (26) for an economy with a large number of agents.

Corollary 2.1. *When the number of agents I goes to infinity, the noise decomposition in Eq. (26) satisfies the following properties:*

- (i) μ and η_i become independent of each other for all $i \in I$,
- (ii) η_i and η_j become independent of each other for all $i, j \in I$,
- (iii) The precision of η_i approaches $\tau \mathcal{L} (\exp(k_i/\mathcal{L}) - 1)$ for all $i \in I$,
- (iv) The precision of μ approaches $\tau \mathcal{L}$.

Proof. See Appendix A. □

Parts (i) and (ii) in the corollary show that the representation in Eq. (26) separates out the original individual error term in each signal (the ϵ_i 's in Corollary 2.3) into the sum of one component that is common across all agents, μ , and a truly idiosyncratic component, η_i . By parts (iii) and (iv) in the corollary, agent i can reduce the idiosyncratic variance of his signal by increasing the amount of resources k_i used for information acquisition. However, agent i cannot reduce the variance of the common component μ , which is determined by the extent of information searchability.

Corollary 2.1 gives a microfoundation for a signal structure that blends together the two common assumptions used in the literature, in which the error terms in the signals are typically

assumed to be either fully private (i.e., purely idiosyncratic noise) or fully public (i.e., purely public noise). A signal structure with similar properties to ours has been assumed in recent work by Manzano and Vives (2011) and Myatt and Wallace (2012).

For a given input of resources k_i , the public-private nature of a signal can be further described as follows. The fraction of a signal’s error term variance that is attributed to the common part is

$$\frac{Var(\mu)}{Var(\epsilon_i)} = 1 - \exp\left(-\frac{k_i}{\mathcal{L}}\right). \quad (28)$$

Hence, the smaller the searchability parameter \mathcal{L} , the more the error terms the signals become “public” across agents. This property of the model is intuitive: the smaller the information content that is available from an information source, the more common the information of the agents who search from it.

It is worth noting that the precision of η_i in Corollary 2.1 is a convex function of k_i . To intuitively understand this, one could interpret η_i as the error term of a signal on $\theta + \mu$. Consider the limiting cases in which \mathcal{L} is either very large or very small. As \mathcal{L} becomes very large, $\theta + \mu$ becomes equivalent to θ because the common component μ vanishes. Then, the precision of η_i becomes equivalent to the precision of the error term ϵ_i in the original signal, which approaches the linear function τk_i as $\mathcal{L} \uparrow \infty$. In contrast, as \mathcal{L} is very small, the error term in the original signal is completely dominated by the common noise (see Eq. (28)). In the limit as $\mathcal{L} \downarrow 0$, the content of the information source becomes akin to a single “small” noisy signal of the form $\theta + \mu$, which can be learnt with any positive amount of resources spent on information search. This case corresponds to an extreme form of convexity for the precision function of η_i . Finite values of \mathcal{L} correspond to cases between these two extremes. For all $\mathcal{L} \in (0, \infty)$, the precision function of η_i is then strictly convex, with curvature that increases for lower values of \mathcal{L} .

3 Application I: Endogenous Information in Coordination Games

We consider endogenous information choice in a beauty contest coordination game of the type popularized by Morris and Shin (2002). Our analysis complements the existing literature (e.g., Hellwig and Veldkamp (2009) and Myatt and Wallace (2012)) by adopting the information technology derived in the previous section. Our contribution is twofold. First, we show that our information acquisition technology leads to qualitatively different implications regarding the nature of the information structure and the existence of multiple equilibria. Second, we provide comparative statics on the different equilibria and searchability of information that are unique to our framework.

3.1 The Setup

There is a continuum of agents indexed by $i \in [0, 1]$ who play a simultaneous move game with the following stages. First, each agent i gathers information, in a way that we specify below, on an aggregate state variable θ . Second, each agent i chooses an action $a_i \in \mathbb{R}$ that is based on the information he has observed. Agent i 's payoff depends on how well his action does at matching the state variable θ as well as the average action $\bar{a} = \int_0^1 a_h dh$. Agent i 's payoff function is assumed to be quadratic:

$$u_i = - (1 - \delta) (\theta - a_i)^2 - \delta (\bar{a} - a_i)^2. \quad (29)$$

The parameter $\delta \in [0, 1]$ in Eq. (29) measures the intensity of agents' coordination motive: larger values of δ reflect larger concerns for an agent to choose an action that is as close as possible to the average action. We assume $\theta \sim N(\bar{\theta}, \tau_\theta^{-1})$. To gather information about θ , each agent in the model allocates a fixed amount of resources K to $J > 1$ independent information sources. Each information source $j \in \{1, \dots, J\}$ is characterized by its own efficiency parameter τ^j and searchability parameter \mathcal{L}^j . Each agent i chooses an allocation of his resources across information sources $k_i = (k_i^1, \dots, k_i^J)$ such that $\sum_j k_i^j \leq K$. The mapping from resources to information is based on the information technology derived in the previous section. When agent i allocates $k_i^j > 0$ resources to information source j , the information obtained through

this source is equivalent to a signal of the form

$$S_i^j = \theta + \epsilon_i^j; \quad \epsilon_i^j \sim N\left(0, \phi^j(k_i^j)^{-1}\right), \quad (30)$$

where the precision function $\phi^j(\cdot)$ is as specified in Eq. (14) in Theorem 2.1,

$$\phi^j(k_i^j) = \tau^j \mathcal{L}^j \left(1 - \exp\left(-\frac{k_i^j}{\mathcal{L}^j}\right)\right).$$

Vice versa, agent i ignores information source j whenever $k_i^j = 0$, in which case the signal S_j^i is pure noise.

The error terms in Eq. (30) are assumed to be independently distributed across information sources. On the other hand, within each information source, the decomposition in Corollary 2.1 implies that we can write each signal S_i^j as

$$S_i^j = \theta + \mu^j + \eta_i^j, \quad (31)$$

where μ^j and η_i^j are independent for all j and i and

$$\mu^j \sim N\left(0, (\tau^j \mathcal{L}^j)^{-1}\right); \quad \eta_i^j \sim N\left(0, \exp(-k^j/\mathcal{L}^j) \phi^j(k_i^j)^{-1}\right). \quad (32)$$

An interpretation of the setup in this section is that of financial analysts or professional forecasters issuing their forecasts on some random variable of interest (e.g., earnings per share on a given stock, a macroeconomic aggregate, a commodity price etc.). In this interpretation, agent i 's action is her forecast, and the average action \bar{a} is the consensus forecast. Resources K would be total working hours. Intuitively, an analyst's payoff depends on the accuracy of her forecast. However, the reputational damage from a wrong forecast is more severe if the analyst's forecast is different from the consensus. The payoff function in Eq. (29) is a second order approximation of these concerns.

3.2 Equilibrium

In line with the literature, we focus on equilibria in which actions are affine functions of the signals, that is, in which agent i 's action takes the form $a_i = \gamma_i^0 + \sum_j \gamma_i^j S_i^j$.⁸ We denote $\gamma_i =$

⁸See Myatt and Wallace (2012) for a discussion of sufficient conditions on the strategy space that ensure this assumption to be without loss of generality.

$(\gamma_i^0, \dots, \gamma_i^J)$ and let Δ be the set of feasible resource allocations, $\Delta = \{k \in \mathbb{R}_+^J \mid \sum_j k^j \leq K\}$. The strategy space is $\Gamma = \Delta \times \mathbb{R}^{J+1}$. An agent's strategy is a pair $(k, \gamma) \in \Gamma$.

We focus on symmetric equilibria in which all agents play the same strategy. When all other agents play some strategy $(\hat{k}, \hat{\gamma})$, agent i 's ex-ante utility from a strategy (k_i, γ_i) equals

$$E(u_i) = -L_1(k_i, \gamma_i) - L_2(\gamma_i, \hat{\gamma}), \quad (33)$$

where $L_1(k_i, \gamma_i)$ and $L_2(\gamma_i, \hat{\gamma})$ are given in Eqs. (B.1)-(B.2) in Appendix B. (Appendix B also contains the derivation of Eq. (33).) $L_1(k_i, \gamma_i)$ is the quadratic loss experienced by an agent when all players play the same strategy. $L_2(\gamma_i, \hat{\gamma})$ is the quadratic loss experienced by an agent when he deviates from other players' strategy. A Symmetric Bayesian Nash Equilibrium (SBNE or equilibrium, hereafter) is a strategy $(\hat{k}, \hat{\gamma})$ such that

$$(\hat{k}, \hat{\gamma}) \in \arg \min_{(k_i, \gamma_i) \in \Gamma} L_1(k_i, \gamma_i) + L_2(\gamma_i, \hat{\gamma}). \quad (34)$$

Since $L_2(\gamma_i, \hat{\gamma})$ vanishes when agent i plays $\gamma_i = \hat{\gamma}$ (and is strictly positive otherwise), a global minimizer of $L_1(k_i, \gamma_i)$ in Eq. (34) is a *payoff maximizing equilibrium*.⁹ In Appendix B (see Lemma B.1) we show that finding a strategy that minimizes $L_1(k_i, \gamma_i)$ reduces to finding an allocation of resources among information sources k^* that satisfies

$$k^* \in \arg \max_{k \in \Delta} G(k), \quad (35)$$

where we define

$$G(k) = \sum_{j=1}^J g_j(k^j); \quad g_j(k^j) = \left[\frac{1 - \delta}{\phi^j(k^j)} + \frac{\delta}{\exp(k^j/\mathcal{L}^j) \phi^j(k^j)} \right]^{-1}. \quad (36)$$

The problem in Eqs. (35)-(36) is that of finding an allocation of resources that maximizes agents' payoffs in a symmetric equilibrium. Because an agents' local deviation from a symmetric strategy profile has no first-order effects on $L_2(\gamma_i, \hat{\gamma})$ (see Eq. (B.3)), k^* in Eq. (35) is the unique SBNE if $G(k)$ is strictly concave in k .

The objective function $G(k)$ in Eq. (36) has an intuitive interpretation. Each function $g_j(k^j)$ is an (weighted, harmonic) average of the precisions of the error term ϵ_i^j of the signal in

⁹We remark that a payoff maximizing equilibrium may not coincide with the first-best if coordination has no social value. See Colombo, Femminis, and Pavan (2014) for a welfare analysis of information acquisition.

Eq. (30) and of the idiosyncratic error term η_i^j in the decomposition in Eq. (31). When agents do not care about other agents' actions, forecasting the fundamental θ is all that matters for agents' utility. In this case, $G(k)$ is simply the sum of signals' precisions ($g_j(\cdot) = \phi^j(\cdot)$ for $\delta = 0$, see Eq. (36)) and k^* is the allocation of resources that gives the most precise forecast of θ . Because the precision functions $\phi^j(\cdot)$ are concave, $G(k)$ is concave, and thus the equilibrium unique, if the coordination motive is sufficiently weak.

On the other hand, coordination motives in actions introduce a distortion. When the coordination motive is strong, agents' utilities depend crucially on whether their actions deviate from the average action. In a symmetric equilibrium, the average action equals $\bar{a} = \hat{\gamma}^0 + \Sigma_j \hat{\gamma}^j (\theta + \mu^j)$, and what matters for predicting \bar{a} is learning about the sums $\theta + \mu^j$. For instance, in the extreme case $\delta = 1$, $G(k)$ is simply the sum of the idiosyncratic precisions ($g_j(k_i^j) = \text{var}(\eta_i^j)^{-1}$ for $\delta = 1$, see Eq. (36) and Eq. (32)) and k^* is the allocation of resources that gives the highest precision on the sums $\theta + \mu^j$. As explained in Section 2.3.1, learning about the sums $\theta + \mu^j$ introduces a source of non-concavity because uncertainty about $\theta + \mu^j$ decreases faster than it does for θ . A strong enough coordination motive makes the problem in Eq. (35) non-concave, which can result in multiple equilibria. For instance, an allocation of resources that constitutes a local (but not global) maximum of $G(k)$ is a SBNE if the cost an agent incurs when moving away from other agents' actions deter deviation.

This discussion suggests that the interplay between the coordination motive and the nature of the information is key for information choices and equilibrium uniqueness. The next propositions analyze this interplay formally.

Proposition 3.1. *(SBNE)(i) When the coordination motive is weak, i.e., for $\delta \in [0, 1/2)$, there exists a unique equilibrium. In equilibrium, information acquisition satisfies*

$$\hat{k}^j(\lambda) = \begin{cases} \mathcal{L}^j \log \left(\frac{\tau^j - 2\lambda\delta(1-\delta) + \sqrt{\tau^j(\tau^j - 4\lambda\delta(1-\delta))}}{2(1-\delta)^2\lambda} \right) & \text{for } 0 < \lambda < \tau^j \\ 0 & \text{for } \lambda \geq \tau^j \end{cases} \quad (37)$$

for some $\lambda > 0$ that is the unique solution to $\Sigma_{j=1}^J \hat{k}^j(\lambda) = K$.

(ii) When the coordination motive is strong, i.e., for $\delta \in [1/2, 1)$, there may be multiple equilibria. An equilibrium allocation of resources is either a local maximum or a critical point of $G(k) = \Sigma_{j=1}^J g_j(k^j)$.

Proof. See Appendix B. □

Proposition 3.1-(i) confirms the intuition from the previous discussion. The equilibrium is unique if the coordination motive is not sufficiently strong. In this equilibrium, agents devote attention to an information source only if this source is sufficiently efficient. As agents care more about other agents' actions, agents allocate their resources among a (weakly) lower number of information sources (i.e., $\frac{d\lambda}{d\delta} > 0$). If information source j is superior to information source i according to Definition 2.3, then information source j gets more resources than i . If an information source is superior to all other information sources and has perfect searchability, it gets all resources.

Proposition 3.1-(ii) reveals the possibility of multiple equilibria when the coordination motive is sufficiently strong. In such case, an equilibrium allocation of resources may have very different properties than the ones discussed above. For example, an equilibrium allocation of resources may favor an inferior information source. The next proposition examines this case in a simplified environment with only two information sources.

Proposition 3.2. (*Inferior information equilibrium when coordination motive is strong*)

Assume there are only two information sources, A and B, such that A is superior to B in that it is relatively more efficient and has perfect searchability ($\tau^A > \tau^B$ and $\mathcal{L}^A = \infty$). Then:

- (i) $\hat{k}^A = K$ is an equilibrium.
- (ii) There exists a threshold $\bar{\mathcal{L}}_N < \infty$ such that $\hat{k}^B = K$ is an equilibrium only if $\mathcal{L}^B \leq \bar{\mathcal{L}}_N$.
- (iii) There exists a threshold $\bar{\mathcal{L}}_S < \infty$ such that, for all $\mathcal{L}^B < \bar{\mathcal{L}}_S$, $\hat{k}^B = K$ is the payoff maximizing equilibrium if the coordination motive is sufficiently strong.

Proof. See Appendix B. □

Since information source A has perfect searchability, the nature of this information is purely private. Then, when $k_i^A = K$ for all agents, an agent's payoffs only depend on the fundamental θ , and deviating from $k_i^A = K$ is costly because A is a superior to B . Devoting all resources to this superior technology is therefore an equilibrium.

The necessary condition in Proposition 3.2-(ii) requires that the inferior information source must be sufficiently public in nature. The intuition is as follows. For $k^B = K$ to be an

equilibrium, it must be a local maximum of $G(k)$ (Proposition 3.1-(ii)). Instead, as \mathcal{L}^B becomes large and information source B becomes private in nature, predicting $\theta + \mu^B$ is the same as predicting θ . Because $\tau^A > \tau^B$, agents would be better off in a symmetric equilibrium in which $\hat{k}^A > 0$.

The intuition for Proposition 3.2-(iii) is the following. If all agents are learning from the superior information source A , then the average action only depends on θ . Instead, if all agents are learning from the inferior information source B , then the average action depends on $\theta + \mu^B$. For $\mathcal{L}^B < \bar{\mathcal{L}}_S$, $k_i^B = K$ gives a more precise source of information about $\theta + \mu^B$ than $k_i^A = K$ does about θ . If agents' concerns about predicting the average action are sufficiently strong, $\hat{k}^B = K$ is an equilibrium that gives higher payoffs to agents than the $\hat{k}^A = K$ equilibrium. (Under the conditions in the proposition, the problem in Eqs. (35)-(36) is strictly convex, and interior equilibria are dominated.)

How strong does the desire for coordination need to be in Proposition 3.2-(iii)? The answer depends on the parameters of the model, including the searchability parameter \mathcal{L}^B . The lower \mathcal{L}^B , the less precise a B -signal is about θ . At the same time, lower \mathcal{L}^B makes a B -signal a more precise source of information about $\theta + \mu^B$. The following corollary shows that the second effect dominates the first one when \mathcal{L}^B is close to the threshold $\bar{\mathcal{L}}_S$. We have:

Corollary 3.1. *(Comparative statics) As \mathcal{L}^B decreases from the threshold $\bar{\mathcal{L}}_S$, a less strong desire for coordination is needed for $\hat{k}^B = K$ to be the payoff maximizing equilibrium.*

Proof. See Appendix B. □

Corollary 3.1 underlies the following surprising result. Since a B -signal's precision is increasing in \mathcal{L}^B , then, over a range of values, an even lower precision of the inferior information source is associated with a *larger* set of parameters for which agents choose this information in the payoff maximizing equilibrium. The left panel of Figure 2 provides an illustration. The figure further shows that the same comparative statics holds when $\hat{k}^B = K$ is a SBNE, without the further requirement of being the payoff maximizing SBNE.

Equilibrium information choices have implications for aggregate volatility, as illustrated by the right panel in Figure 2. The aggregate action is perfectly correlated with the fundamental when resources are fully invested in the superior information. Instead, this correlation is

significantly lower than one in the inferior information equilibrium because of the common noise μ^B . As a result, the volatility of the average action is significantly higher in the $\hat{k}^B = K$ equilibrium than it is in the $\hat{k}^A = K$ equilibrium, and this difference is more pronounced for lower values of the searchability parameter \mathcal{L}^B .

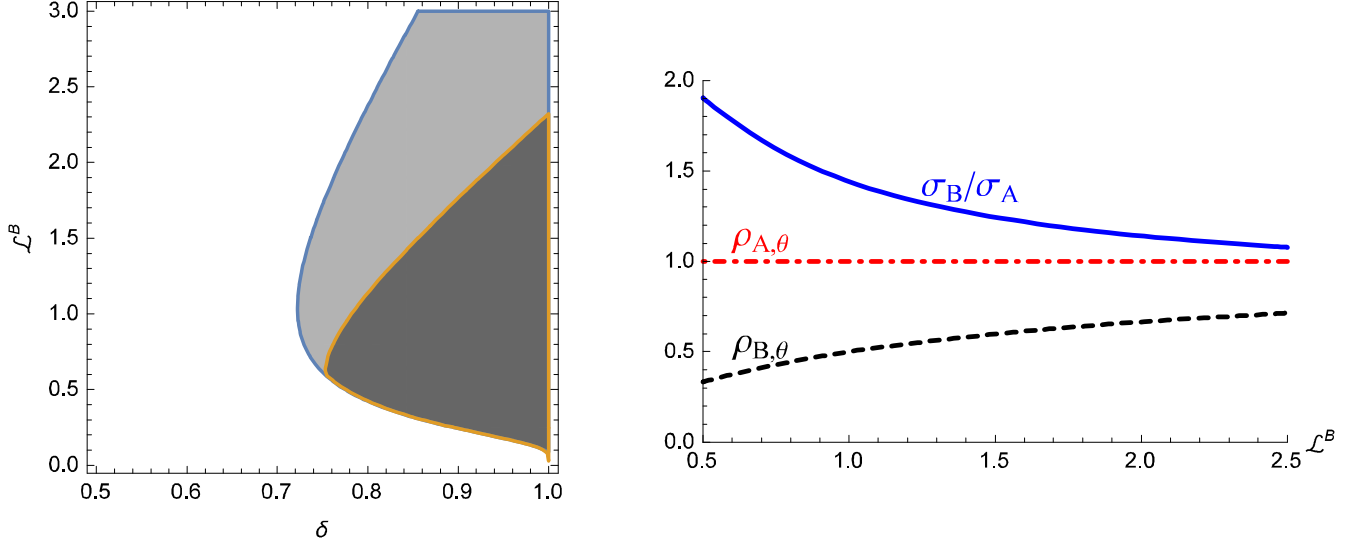


FIGURE 2. Left panel: light grey area: $\hat{k}^B = K$ is a SBNE; dark grey area: $\hat{k}^B = K$ is the payoff maximizing SBNE. Right panel: thick line, σ_B/σ_A : relative volatility of the aggregate action across $\hat{k}^B = K$ and $\hat{k}^A = K$ equilibria; dashed (dot-dashed) line, $\rho_{B,\theta}$ ($\rho_{A,\theta}$): correlation coefficient between the average action \bar{a} and θ in the $\hat{k}^B = K$ ($\hat{k}^A = K$) equilibrium. Parameter values: $\tau_\theta = \tau^A = K = 1$, $\tau^B = 0.8$ in both panels and $\delta = 0.8$ in the right panel.

In the interpretation of this model as one of financial analysts or professional forecasters, the superior information technology could be fundamental analysis, and the inferior information source could be information originating from the media (e.g., social media, investors' online chat rooms, popular business TV shows). Proposition 3.2 and Corollary 3.1 describe an equilibrium in which analysts gather all their information from the inferior source. In this equilibrium, the informational content of the consensus forecast is

$$Var[\theta|\bar{a}]^{-1} = \frac{\tau_\theta}{1 - corr(\theta, \bar{a})^2},$$

where $\text{corr}(\theta, \bar{a})$ denotes the correlation coefficient between θ and \bar{a} . Hence, the correlation coefficients in Figure 2 measure the informational efficiency of the equilibrium outcome. While the consensus forecast reveals the fundamental perfectly in the $\hat{k}^A = K$ equilibrium, the equilibrium outcome is informationally inefficient in the $\hat{k}^B = K$ equilibrium.

3.3 Relation to the literature

The analysis in this section relates very closely to Hellwig and Veldkamp (2009) and Myatt and Wallace (2012). Both papers consider endogenous information acquisition in a beauty contest coordination game.

A key message in Hellwig and Veldkamp (2009) is that the endogenous choice of public information generates multiple equilibria. The idea is that a public signal is more valuable than a private signal because it carries information both about the fundamental and about what other agents have learned (and, hence, about what other agents will do). However, this second effect depends on whether the public signal has been acquired by others or not, and this leads to multiple equilibria.¹⁰

A very different message emerges from Myatt and Wallace (2012), who assume a signal structure equivalent to Eq. (31) in which costly information acquisition from an information source reduces the idiosyncratic noise (but not the common noise). In their setup, the equilibrium is unique. The key difference is that the correlation in public information is bounded away from zero in Hellwig and Veldkamp (2009), while in Myatt and Wallace (2012) the publicity of a signal depends on agents' information choices and the first bits of information are effectively private. As Myatt and Wallace (2012) put it, "this smooths out the first step of the information acquisition process and eliminates multiple equilibria, even though the informative signals actually acquired in equilibrium may be relatively public in nature."

The message from Proposition 3.1 is somewhat intermediate between these two papers. In our setup, the endogeneity of the signal structure in Eq. (31) leads to non-concavities that are absent in Myatt and Wallace (2012). The endogenous publicity of signals guarantees a unique equilibrium only if the coordination motive is sufficiently weak.

¹⁰This result also holds when acquisition of public information is "near continuous," in which case the value of information is kinked at the point where other agents have stopped learning from the public source. Hence, there can be many equilibria (a continuum, in fact).

4 Application 2: Portfolio Choice and Asset Prices with Endogenous Information

In this section, we study an example of resource allocations under imperfect information searchability in the context of portfolio optimization and financial equilibrium. There is a large volume of literature on financial equilibrium with endogenous information acquisition (e.g., Grossman and Stiglitz (1980), Peress (2004), Peng (2005), Van Nieuwerburgh and Veldkamp (2009), Van Nieuwerburgh and Veldkamp (2010) and Mondria (2010)). Our results here complement those in the existing literature by suggesting an alternative mechanism—information search—that affects investors’ optimal portfolio choice and asset prices.

We have two main goals in this section. The first goal is to study the impact of information searchability on an agent’s resource allocation and portfolio choice problem. The second goal is to embed these choices in a noisy rational expectations equilibrium and study the impact of information searchability on equilibrium prices.

4.1 Optimal Resource Allocation and Portfolio Choice

Consider a competitive investor who wants to allocate his resources optimally in order to maximize his expected utility from investment in a one-period setup ($t = 0, 1$). There are N risky assets in the economy. Each asset $j \in \{1, 2, \dots, N\}$ pays θ^j at $t = 1$, where θ^j follows a normal distribution with mean $\bar{\theta}^j$ and variance $1/\tau_\theta^j$. Payoffs θ^j ’s are independent of each other. There also exists a riskless asset whose gross return is normalized to one. We denote p^j to be the price of each risky asset in the market. To focus on the effects of learning from costly information, we assume that the price of each asset j does not provide any payoff relevant information. For concreteness, we set each p^j equal to the payoff mean, i.e., $p^j = E[\theta^j]$.¹¹ We will relax this assumption in the next subsection where we study a noisy rational expectations equilibrium.

The investor is endowed with an initial wealth w_0 , and has a CARA utility function such that $u(w_1) = -\frac{1}{\gamma} \exp(-\gamma w_1)$, where w_1 is his wealth at $t = 1$. At $t = 0$, he acquires information

¹¹One can consider a situation where the trader submits orders given prices posted by competitive risk-neutral market makers.

on the risky assets, then forms a portfolio that consists of the risky assets and the riskless asset. At $t = 1$, he receives the realized payoff of his portfolio.

The investor is also endowed with a total amount of resources K which can be allocated to gather information about the risky assets. k^j denotes the amount of resources allocated on asset $j \in \{1, 2, \dots, N\}$. An allocation of resources across risky assets is feasible for the investor if it satisfies the constraint

$$\sum_{j=1}^N k^j \leq K. \quad (38)$$

The mapping from resources to information is based on the information technology derived in Section 2. Here τ^j and \mathcal{L}^j denote, respectively, the efficiency and searchability parameters for asset j . By Theorem 2.3, the information collected by the investor for each asset j is equivalent to a noisy signal on the fundamental value of each asset j ,

$$S^j = \theta^j + \epsilon^j, \quad (39)$$

where ϵ^j follows a normal distribution with mean zero and precision $\phi^j(k^j)$ which is defined in Eq. (14):

$$\phi^j(k_i^j) = \tau^j \mathcal{L}^j \left(1 - \exp\left(-\frac{k_i^j}{\mathcal{L}^j}\right) \right).$$

For a given allocation of resources and signals' realizations, the agent's optimal portfolio choice in asset $j = 1, \dots, N$ is given by the standard CARA-Gaussian demand, which for $p^j = E(\theta^j)$ equals

$$x^j = \frac{\phi^j(k^j)(S^j - p^j)}{\gamma}. \quad (40)$$

For notational convenience, we define $\hat{\tau}^j = \tau^j / \tau_\theta^j$ as the normalized signal efficiency. Ex ante, the investor allocates his resources K while anticipating his asset demand in Eq. (40). By solving this resource allocation problem, we find:

Proposition 4.1. *(Optimal information choice) There exists a unique optimal allocation of resources for the risky assets such that the optimal allocation k^j is given by*

$$k^j(\lambda) = \begin{cases} \mathcal{L}^j \log\left(\frac{\hat{\tau}^j + \hat{\tau}^j \mathcal{L}^j}{\lambda + \hat{\tau}^j \mathcal{L}^j}\right) & \text{if } 0 < \lambda < \hat{\tau}^j \\ 0 & \text{if } \lambda \geq \hat{\tau}^j \end{cases} \quad (41)$$

where λ is a positive constant. Furthermore, λ decreases in K and increases in \mathcal{L}^j for all j with $\hat{\tau}^j > \lambda$.

Proof. See Appendix C. □

The allocation of resources in Proposition 4.1 is governed by the endogenously-determined multiplier λ , which is interpreted as the shadow price of the resource constraint. From Eq. (41) we can deduce the following. First, the resource allocation k^j on each asset j decreases as the shadow price λ increases. Second, the number of assets that receive a positive allocation of resources (i.e., $k^j > 0$) weakly decreases in λ . This in turn affects the portfolio choice x^j in Eq. (40), and results in a portfolio that is more concentrated (resp., diversified) as the shadow price λ increases (resp., decreases).¹²

Proposition 4.1 further demonstrates that the shadow cost λ decreases in the investor's total amount of resource K , and increases in the searchability of each asset. Therefore, ceteris paribus, a smaller amount of resources K or an increase in information searchability for some assets results in the investor's portfolio being more concentrated.

In the next corollary we further illustrate the comparative statics of changes in searchability in one asset.

Corollary 4.1. (*Attention crowding out*) Consider an improvement in information searchability for an asset to which the investor allocates positive resources. Then: (i) the resources allocated to the other assets in the portfolio strictly decrease (i.e., $\frac{dk^r}{d\mathcal{L}^j} < 0$ for any asset $r \neq j$ with $k^r > 0$); and (ii) the resource allocation to the asset with improved searchability strictly increases (i.e., $\frac{dk^j}{d\mathcal{L}^j} > 0$).

Corollary 4.1 implies that the investor puts less resources on other assets if one asset becomes more searchable. This is quite intuitive. If the informational environment for an asset already in the portfolio becomes richer, information about this asset can be acquired more efficiently. As a result, the investor will increase attention to it in order to exploit further private information. This effect naturally crowds out attention on other assets. Therefore, the portfolio becomes more concentrated.

¹²Because this setup is one of purely speculative trading, having no private information on an asset implies that the asset has zero weight in the investor's portfolio.

4.2 A Noisy Rational Expectations Equilibrium

What is the impact of information searchability on the cross section of risk premia and liquidity of risky assets? To answer this question, we embed the resource allocation and portfolio choice of Section 4.1 in a noisy rational expectations equilibrium framework.

There is a continuum of homogenous investors indexed by $i \in [0, 1]$. Each investor has CARA utility with risk aversion γ and is endowed with an initial wealth w_0 and an amount of resources K . In contrast to the model of Section 4.1, equilibrium prices will partially reveal the investors' private information. We assume that the supply of each asset j is given by z^j which follows a normal distribution with mean \bar{z}^j and variance $1/\tau_z^j$. The noise in the supply can arise due to non-informational trades such as liquidity trading (or noise trading) and is assumed to be independent of all other random variables in the model.

Due to Corollary 2.1, we can represent each signal S_i^j (i.e., agent i 's signal on asset j) as follows:

$$S_i^j = \theta^j + \mu^j + \eta_i^j, \quad (42)$$

where the common error term μ^j and the idiosyncratic error term η_i^j are independent for all j and i and

$$\mu^j \sim N\left(0, (\tau^j \mathcal{L}^j)^{-1}\right); \quad \eta_i^j \sim N\left(0, \exp(-k^j / \mathcal{L}^j) \phi^j(k_i^j)^{-1}\right).$$

As in the standard noisy rational expectation equilibrium models of Grossman and Stiglitz (1980), Hellwig (1980) and Admati (1985), we focus on a linear equilibrium where the price function is given by an affine function of fundamentals and noise. We summarize the equilibrium at the trading stage as follows:

Lemma 4.1. (*Financial market equilibrium*) *There exists a unique linear equilibrium in which the price for each asset $j \in \{1, 2, \dots, N\}$ is given by*

$$p^j = f_1^j(\theta^j + \mu^j) - f_2^j z^j, \quad (43)$$

where f_1^j and f_2^j are constants.

Proof. See Appendix C. □

Now, we turn to the overall equilibrium of the model. For simplicity, we focus on symmetric equilibria in which information choices are the same across agents. The ex-ante optimization

problem of each investor is similar to the one in Proposition 4.1. However, the problem now involves learning the information that is aggregated and transmitted via the equilibrium prices in Eq. (43). Investors' information choices determine how much information asset prices transmit, which in turn influences an investor's information choices. An equilibrium allocation of information is a fixed point of this problem. The following proposition shows that a symmetric equilibrium always exists under some given level of parameter values.

Proposition 4.2. *(Overall equilibrium) For sufficiently small τ_z^j , there always exists an overall equilibrium. In equilibrium, there exists a unique constant λ such that each agent i allocates k_i^j on each asset j given λ as follows:*

$$k_i^j(\lambda) = \begin{cases} \mathcal{L}^j \log \left(A^j + \sqrt{(A^j)^2 - B^j} \right) & \text{if } 0 < \lambda < \bar{\lambda}^j \\ 0 & \text{if } \lambda \geq \bar{\lambda}^j, \end{cases} \quad (44)$$

where

$$\bar{\lambda}^j = \frac{\hat{\tau}^j}{\left(1 + (\tau^j \mathcal{L}^j)^{-1} \tau_p^j\right) \left(1 + \left(\frac{1}{\tau_\theta^j} + (\tau^j \mathcal{L}^j)^{-1}\right) \tau_p^j\right)}; \quad (45)$$

$$A^j = \frac{1}{2} \left(\frac{\hat{\tau}^j}{\lambda} + \hat{\tau}^j \mathcal{L}^j \right) - (\tau^j \mathcal{L}^j)^{-1} \tau_p^j; \quad (46)$$

$$B^j = (\tau^j \mathcal{L}^j)^{-1} \tau_p^j \left[(\tau^j \mathcal{L}^j)^{-1} \tau_p^j - \frac{\hat{\tau}^j \mathcal{L}^j}{1 + \hat{\tau}^j \mathcal{L}^j} \right]; \quad (47)$$

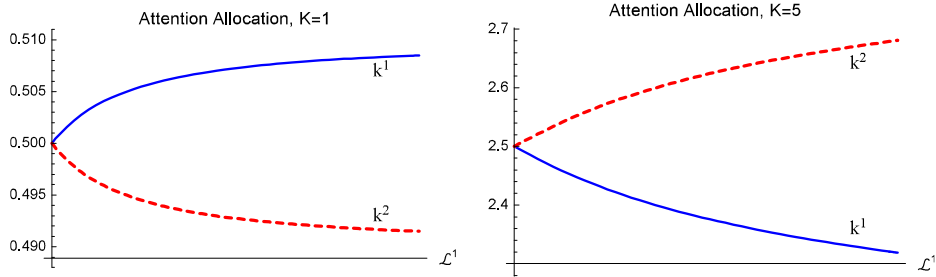
$$\tau_p^j = \left(\frac{f_1^j}{f_2^j} \right)^2 \tau_z^j. \quad (48)$$

Proof. See Appendix C. □

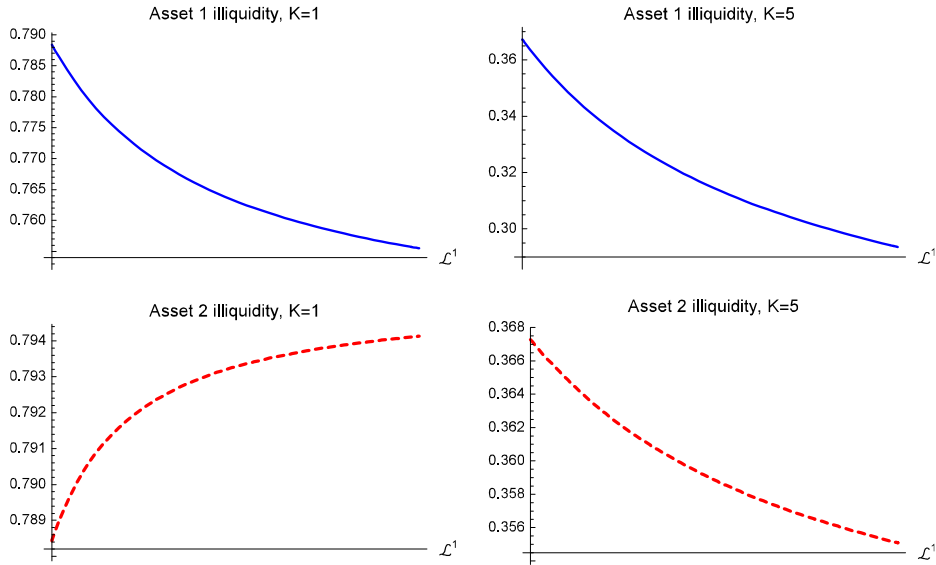
We remark that the term τ_p^j in Eq. (48) captures the precision with which price p^j reveals $\theta^j + \mu^j$, the common part of the investors' information on asset j . In general, information revelation through prices reduces investors' incentives to acquire information. This effect is illustrated by the threshold value $\bar{\lambda}^j$ in Eq. (45) which decreases in the precision τ_p^j . Intuitively, prices must not be too informative for it be optimal to spend resources on private information acquisition. On the other hand, in the limit case in which τ_z^j approaches zero and prices

become very noisy, the equilibrium resource allocation in Proposition 4.2 converges to the one in Proposition 4.1 with no learning from prices.

Figure 3 shows a numerical example with two risky assets. We illustrate the comparative statics of increasing the searchability parameter of asset 1 while keeping that of asset 2 at the initial level.



(i) Equilibrium resource allocations across various levels of information searchability



(ii) Assets' illiquidity across various levels of information searchability

FIGURE 3. This figure plots the equilibrium resource allocation $\{k^j\}_{j=1,2}$ (panel (i)) and assets' equilibrium illiquidity coefficients f_2^j (panel (ii)) as a function of \mathcal{L}^1 for low (left column) and high (right column) values of the investors' resources K . Parameter values are $\tau_\theta^1 = \tau_\theta^2 = \gamma = 1$, $\tau^1 = \tau^2 = 2$, $\tau_z^1 = \tau_z^2 = 2$ and $\mathcal{L}^2 = 5$.

Panel (i) in the figure shows how investors change their resource allocations in equilibrium. As information on asset 1 becomes more searchable, Corollary 4.1 suggests that the resource allocation to this asset should increase. However, in equilibrium there is an opposing force related to the externality of information revelation through prices. As \mathcal{L}^1 increases, the precision of agents' information about asset 1 increases (given $k^1 > 0$). Keeping information choices fixed, more precise information is aggregated and partially revealed through the price p^1 , thereby reducing the incentives to gather information on asset 1. When this force is sufficiently strong, the partial equilibrium comparative statics of Corollary 4.1 may actually be reversed. Figure 3 shows that investors' allocation of resources to asset 1 increases when the size of total resources K is small whereas it decreases when K is large. Intuitively, a larger amount of resources spent on information acquisition makes prices more informative and is associated with a stronger information externality.

Panel (ii) of Figure 3 shows the implications of these information choices for asset prices. We measure market illiquidity by f_2^j , which is the price coefficient on noisy supply in Eq. (43).¹³ The market becomes more liquid if the investors are more confident about fundamentals of the traded asset. As the precision of information for asset 1 exogenously increases (i.e., as \mathcal{L}^1 increases), liquidity for this asset should improve. The top row of panel (ii) confirms this intuitive result in an equilibrium framework with endogenous information choice. The bottom row of panel (ii) shows a more interesting result. We remark that since the two assets are independent, any effect of an increase in \mathcal{L}^1 on asset 2 is only due to its effect on the information choices. The figure shows how such an “informational spillover” operates on the illiquidity of asset 2. When the information externality is weak (low K), the attention crowding out effect (i.e., k^2 decreases in \mathcal{L}^1) results in increased investors' uncertainty on asset 2. Hence, the informational spillover on market liquidity for the second asset is negative. The opposite effect arises when the information externality is strong (high K), and an increase in \mathcal{L}^1 leads to more resources being allocated to asset 2. In this case, an increase in information searchability for the first asset results in an improvement in liquidity for both assets.¹⁴

¹³This illiquidity measure reflects the price sensitivity to changes in the asset's random supply. This measure is often used in the finance literature following the seminal paper by Kyle (1985).

¹⁴Similar results hold with respect to the informational efficiency of prices, defined as $Var[\theta^j|p^j]^{-1}$. That is, $Var[\theta^1|p^1]^{-1}$ increases in \mathcal{L}^1 while $Var[\theta^2|p^2]^{-1}$ decreases in \mathcal{L}^1 for lower values of K and increases in \mathcal{L}^1 for

4.3 Relation to the literature

The empirical evidence shows that investors systematically under-diversify their portfolios. Furthermore, retail investors are also subject to significant home biases in their portfolio choices. What causes such under-diversification? The existing literature has suggested various reasons: (i) informational frictions (e.g., Van Nieuwerburgh and Veldkamp (2009), Van Nieuwerburgh and Veldkamp (2010)), (ii) institutional barriers (e.g., Black (1974)), and (iii) behavioral biases such as familiarity bias (e.g., Portes and Rey (2005)). For example, Van Nieuwerburgh and Veldkamp (2009) employ the Kreps and Porteus (1978) framework to induce preference for an early resolution of uncertainty, and this creates benefits of specialization among investors. Such specialization benefits lead to portfolio concentration.

In our analysis, increased frictions in information search cause more concentrated portfolios. This result is line with the literature that connects informational frictions to under-diversification. Unlike the existing literature, however, our paper relates the lack of portfolio diversification to the investors' availability of resources for information search. Given that retail investors are likely to have less resources for information search than institutional investors, our model predicts higher portfolio concentration among retail investors relative to institutional investors. This fits the well-documented empirical observation that retail investors tend to under-diversify their portfolios more than institutional investors.

Our model also predicts that increasing searchability of one asset may crowd out investing in other assets by taking away investors' attention. For instance, if assets traded in the home market have superior information sources for domestic investors, a home bias should arise as a result of this attention crowding out effect. Therefore, our model contributes to the literature by suggesting an alternative mechanism of specialization and portfolio concentration.

Finally, our analysis highlights a new channel for liquidity spillovers across assets and relates the sign of such spillovers to the investors' endowment of resources. More specifically, our results suggest the following empirical prediction: that differences in the availability of information across stocks should be associated with larger cross-sectional differences in liquidity and informational efficiency when investors' resources are more limited. Because small stocks are mostly held by retail investors with smaller resources than institutional investors, these informational spillovers should be more pronounced for small firms.

higher values of K .

5 Conclusion

In our paper, we develop a microfounded framework of information acquisition in which searchable information is limited. Our framework on learning under imperfect information searchability is based on a simple intuition: As an agent keeps searching for new information, it is likely that he would encounter some overlapping pieces of information from the past searching activities. Furthermore, other agents searching for information from the same source would face the same difficulty in collecting new information, thus, they are more likely to end up with similar information in case the amount of searchable information is smaller. We formalize this idea by employing an urn model where signals are drawn with replacement. This allows us to develop a framework in which both the concavity of signal precision and the correlation among signals increase as information becomes less searchable. Using an asymptotic approach, we construct a tractable mapping from resource allocations to the precision and the correlation of agents' acquired information under varying degrees of searchable information.

We study two economic applications with endogenous information acquisition using our model. Our first application is a “beauty contest” coordination game with endogenous information. We find that agents may prefer an inferior information source with less searchable information due to coordination motives. When the coordination motive is sufficiently strong, there exists an equilibrium in which all agents choose to focus on the inferior information source. Because less searchable information leads to more covariance, such equilibrium outcome becomes more likely precisely when the inferior information source becomes more inefficient. In the second application with a multi-asset market, we study a noisy rational expectations equilibrium model in which investors optimally allocate resources across risky assets. We find that improved searchability on one asset can crowd out attention on other assets, thereby resulting in portfolio concentration. Furthermore, such tendency is more pronounced when investors are more constrained in resources. Our results shed further light on under-diversification phenomena while at the same time having implications for cross-sectional differences in liquidity across assets.

Appendix A

Proof of Lemma 2.2: We prove this lemma in a similar fashion as in standard proofs of the strong law of large numbers.¹⁵ The major difference of the proof from the standard case is that samples of the random variables from the population allow redundancy at varying rates as the number of samples increases.

Let L denote the number of distinct signals in \mathbf{L} , i.e., $L = \lfloor \frac{\mathcal{L}}{c} \rfloor$. We also denote l to be the number of collected signals from \mathbf{L} , i.e., $l = \lfloor \frac{k}{c} \rfloor$. For each $m \in \{1, 2, \dots, L\}$, we define $\tilde{h}^m(k; c)$ to be one if signal s^m is collected eventually, and zero otherwise. Then, we have $\tilde{h}(k; c) = \sum_{m=1}^L \tilde{h}^m(k; c)$, and

$$E[\tilde{h}^m(k; c)] = Pr(\tilde{h}^m(k; c) = 1) = 1 - \left(\frac{L-1}{L}\right)^l. \quad (\text{A.1})$$

By Markov's inequality, we have

$$Pr \left[\left| \tilde{h}(k; c) - E[\tilde{h}(k; c)] \right| \geq \alpha \right] \leq \frac{c^4 E \left[\left| \tilde{h}(k; c) - E[\tilde{h}(k; c)] \right|^4 \right]}{\alpha^4}. \quad (\text{A.2})$$

We first prove that $c^2 E \left[\left| \tilde{h}(k; c) - E[\tilde{h}(k; c)] \right|^4 \right]$ converges as $c \rightarrow 0$. That is, the r.h.s. would be less than $\frac{c^2 M}{\alpha^4}$ for sufficiently small c for some positive constant M . This will allow us to have the desired result.

We now drop the arguments in $\tilde{h}(k; c)$ and $\tilde{h}^m(k; c)$ for notational convenience throughout this proof. Observe that

$$E \left[\left| \tilde{h} - E[\tilde{h}] \right|^4 \right] = E \left[\tilde{h}^4 \right] - 4E \left[\tilde{h}^3 \right] E \left[\tilde{h} \right] + 6E \left[\tilde{h}^2 \right] E \left[\tilde{h} \right]^2 - 4E \left[\tilde{h} \right]^4 + E \left[\tilde{h} \right]^4. \quad (\text{A.3})$$

Then, we can obtain the exact expression for Eq. (A.3) by obtaining each element in it separately as follows:

$$E \left[\tilde{h}^2 \right] = LE \left[(\tilde{h}^m)^2 \right] + L(L-1)E \left[\tilde{h}^m \tilde{h}^n \right], \quad (\text{A.4})$$

$$E \left[\tilde{h}^3 \right] = LE \left[(\tilde{h}^m)^3 \right] + \binom{3}{2} L(L-1)E \left[(\tilde{h}^m)^2 \tilde{h}^n \right] + L(L-1)(L-2)E \left[\tilde{h}^m \tilde{h}^n \tilde{h}^x \right], \quad (\text{A.5})$$

$$\begin{aligned} E \left[\tilde{h}^4 \right] &= LE \left[(\tilde{h}^m)^4 \right] + \binom{4}{3} L(L-1)E \left[(\tilde{h}^m)^3 \tilde{h}^n \right] + \frac{1}{2} \binom{4}{2} L(L-1)E \left[(\tilde{h}^m)^2 (\tilde{h}^n)^2 \right] \\ &\quad + \binom{4}{2} L(L-1)(L-2)E \left[(\tilde{h}^m)^2 \tilde{h}^n \tilde{h}^x \right] + L(L-1)(L-2)(L-3)E \left[\tilde{h}^m \tilde{h}^n \tilde{h}^x \tilde{h}^y \right]. \end{aligned} \quad (\text{A.6})$$

¹⁵See, for example, Billingsley (1979) for the standard proofs of the strong law of large numbers.

Because $(h^m)^r = h^m$ for all $r \in \mathbb{N}$, we have $E[(\tilde{h}^m)^r] = E[\tilde{h}^m]$, $E[(\tilde{h}^m)^r(\tilde{h}^n)^q] = E[\tilde{h}^m\tilde{h}^n]$, and $E[(\tilde{h}^m)^r(\tilde{h}^n)^q(\tilde{h}^x)^s] = E[\tilde{h}^m\tilde{h}^n\tilde{h}^x]$ for any $r, q, s \in \mathbb{N}$. By substituting Eqs. (A.4), (A.5) and (A.6) into Eq. (A.3), we have

$$E\left[\left|\tilde{h} - E[\tilde{h}]\right|^4\right] = LE\left[\tilde{h}^m\right] + (3L^2 - 7L)E\left[\tilde{h}^m\tilde{h}^n\right] - 6(L^2 + 2L)E\left[\tilde{h}^m\tilde{h}^n\tilde{h}^x\right] + 3(L^2 - 2L)E\left[\tilde{h}^m\tilde{h}^n\tilde{h}^x\tilde{h}^y\right]. \quad (\text{A.7})$$

We denote S to be the set of outcomes from drawing of l signals from the set \mathbf{L} (i.e., the urn). Then, we have $|S| = L^l$ because there are L signals in the set \mathbf{L} .¹⁶ We define A_m to be an event where signal i is not drawn within l trials (i.e., \tilde{h}^m is equal to zero). Then, the expectation of the product between the random variables \tilde{h}^m and \tilde{h}^n is given by

$$E\left[\tilde{h}^m\tilde{h}^n\right] = Pr(\tilde{h}^m\tilde{h}^n = 1) = Pr(A_m^c \cap A_n^c) = \frac{|A_m^c \cap A_n^c|}{|S|}. \quad (\text{A.8})$$

Using the inclusion–exclusion principle, we obtain¹⁷

$$E\left[\tilde{h}^m\tilde{h}^n\right] = \frac{|S| - 2|A_m^c| + |A_m^c \cap A_n^c|}{|S|} = 1 - \frac{2(L-1)^l - (L-2)^l}{L^l} = 1 - 2\left(1 - \frac{1}{L}\right)^l + \left(1 - \frac{2}{L}\right)^l. \quad (\text{A.10})$$

Therefore, taking the limit of c in Eqs. (A.1) and (A.10) yields

$$\lim_{c \rightarrow 0} E\left[\tilde{h}^m\right] = 1 - \exp\left(-\frac{k}{\mathcal{L}^c}\right), \quad (\text{A.11})$$

$$\lim_{c \rightarrow 0} E\left[\tilde{h}^m\tilde{h}^n\right] = \left(1 - \exp\left(-\frac{k}{\mathcal{L}^c}\right)\right)^2. \quad (\text{A.12})$$

In a similar fashion as in Eq. (A.10), we obtain the followings using the inclusion–exclusion principle:

$$E\left[\tilde{h}^m\tilde{h}^n\tilde{h}^x\right] = Pr(\tilde{h}^m\tilde{h}^n\tilde{h}^x = 1) = 1 - \frac{3(L-1)^l - 3(L-2)^l + (L-3)^l}{L^l}, \quad (\text{A.13})$$

¹⁶ $|A|$ indicates the cardinality of a set A .

¹⁷Suppose that there are finite sets A_1, A_2, \dots, A_M that belong to a set S . Then, the inclusion–exclusion principle states that

$$|\cap_{m=1}^M A_m^c| = |S| - \sum_{m=1}^M |A_m| + \sum_{1 \leq m < n \leq M} |A_m \cap A_n| - \sum_{1 \leq m < n < r \leq M} |A_m \cap A_n \cap A_r| + \dots + (-1)^M |\cap_{m=1}^M A_m|. \quad (\text{A.9})$$

$$E \left[\tilde{h}^m \tilde{h}^n \tilde{h}^x \tilde{h}^y \right] = Pr(\tilde{h}^m \tilde{h}^n \tilde{h}^x \tilde{h}^y) = 1 - \frac{4(L-1)^l - 6(L-2)^l + 4(L-3)^l - (L-4)^l}{L^l}. \quad (\text{A.14})$$

Then, taking the limit of c in Eqs. (A.13) and (A.14) yields the followings:

$$\lim_{c \rightarrow 0} E \left[\tilde{h}^m \tilde{h}^n \tilde{h}^x \right] = \left(1 - \exp \left(-\frac{k}{\mathcal{L}} \right) \right)^3, \quad (\text{A.15})$$

$$\lim_{c \rightarrow 0} E \left[\tilde{h}^m \tilde{h}^n \tilde{h}^x \tilde{h}^y \right] = \left(1 - \exp \left(-\frac{k}{\mathcal{L}} \right) \right)^4. \quad (\text{A.16})$$

Multiplying c^2 to Eq. (A.7) and taking the limit of c yields

$$\lim_{c \rightarrow 0} c^2 E \left[\left| \tilde{h} - E[\tilde{h}] \right|^4 \right] = 3\mathcal{L}^2 \exp \left(-\frac{2k}{\mathcal{L}} \right) \left(1 - \exp \left(-\frac{k}{\mathcal{L}} \right) \right)^2. \quad (\text{A.17})$$

Given a positive real number δ , let $\bar{\mathcal{L}}$ denote $3\mathcal{L}^2 \exp \left(-\frac{2k}{\mathcal{L}} \right) \left(1 - \exp \left(-\frac{k}{\mathcal{L}} \right) \right)^2 + \delta$. Then, there exists \bar{c} such that $c^2 E \left[\left| \tilde{h} - E[\tilde{h}] \right|^4 \right] < \bar{\mathcal{L}}$. Therefore, there exists $N > 0$ such that for all $n \geq N$ and $n \in \mathbb{N}$ we have

$$Pr \left[\left| \frac{1}{n} \tilde{h} - \frac{1}{n} E[\tilde{h}] \right| \geq \alpha \right] < \frac{\bar{\mathcal{L}}}{n^2 \alpha^4}. \quad (\text{A.18})$$

Then, the first Borel-Cantelli lemma implies that

$$Pr \left[\lim_{n \rightarrow \infty} \left| \Phi \left(\tilde{h}(k; \frac{1}{n}) \right) - \phi(k) \right| < \alpha \right] = 1, \quad (\text{A.19})$$

or equivalently

$$Pr \left[\lim_{c \rightarrow 0} \left| \Phi \left(\tilde{h}(k; c) \right) - \phi(k) \right| < \alpha \right] = 1. \quad \blacksquare \quad (\text{A.20})$$

Proof of Lemma 2.3: The proof is parallel with Lemma 2.2. Let L to be the number of distinct signals in \mathbf{L} , i.e., $L = \lfloor \frac{\mathcal{L}}{c} \rfloor$. We also denote l^i and l^j to be the number of signals collected by agent i and j from \mathbf{L} , respectively, i.e., $l^i = \lfloor \frac{k^i}{c} \rfloor$ and $l^j = \lfloor \frac{k^j}{c} \rfloor$. For each $m \in \{1, 2, \dots, L\}$, we define we define $\tilde{h}_{i,j}^m(k_i; c)$ to be one if signal s^m belongs to the group of the commonly collected signals $H_{i,j}$, and zero otherwise. We also define $\tilde{h}_i^m(k_i; c)$ (or $\tilde{h}_j^m(k_j; c)$) to be one if signal s^m is collected by agent i (or j), and zero otherwise. Then, we have

$$\tilde{h}_{i,j}(k_i, k_j; c) = \sum_{m=1}^L \tilde{h}_{i,j}^m(k_i, k_j; c) = \sum_{m=1}^L \tilde{h}_i^m(k_i; c) \tilde{h}_j^m(k_j; c). \quad (\text{A.21})$$

Because $\tilde{h}_i^m(k_i; c)$ and $\tilde{h}_j^m(k_j; c)$ are independent, we get

$$\begin{aligned} E[\tilde{h}_{i,j}(k_i, k_j; c)] &= \sum_{m=1}^L Pr(\tilde{h}_i^m(k_i; c)\tilde{h}_j^m(k_j; c) = 1) = \sum_{m=1}^L Pr(\tilde{h}_i^m(k_i; c) = 1)Pr(\tilde{h}_j^m(k_j; c) = 1) \\ &= L \left[\left(1 - \left(\frac{L-1}{L}\right)^{l_i}\right) \left(1 - \left(\frac{L-1}{L}\right)^{l_j}\right) \right]. \end{aligned} \quad (\text{A.22})$$

We can represent Eq. (A.22) given k_i and k_j as follows:

$$E[\tilde{h}_{i,j}(k_i, k_j; c)] = \lfloor \frac{\mathcal{L}}{c} \rfloor \left[\left(1 - \left(1 - \frac{1}{\lfloor \frac{\mathcal{L}}{c} \rfloor}\right)^{\lfloor \frac{k_i}{c} \rfloor}\right) \left(1 - \left(1 - \frac{1}{\lfloor \frac{\mathcal{L}}{c} \rfloor}\right)^{\lfloor \frac{k_j}{c} \rfloor}\right) \right]. \quad (\text{A.23})$$

Multiplying c to Eq. (A.23) and taking the limit of c yields

$$\lim_{c \rightarrow 0} E[c\tilde{h}_{i,j}(k_i, k_j; c)] \rightarrow \mathcal{L} \left(1 - \exp\left(-\frac{k_i}{\mathcal{L}}\right)\right) \left(1 - \exp\left(-\frac{k_j}{\mathcal{L}}\right)\right). \quad (\text{A.24})$$

We now drop the arguments in $\tilde{h}_{i,j}(k_i, k_j; c)$ and $\tilde{h}_{i,j}^m(k_i, k_j; c)$ for notational convenience throughout this proof.

By Markov's inequality, we have

$$Pr \left[\left| c\tilde{h}_{i,j} - E[c\tilde{h}_{i,j}] \right| \geq \alpha \right] \leq \frac{c^4 E \left[\left| \tilde{h}_{i,j} - E[\tilde{h}_{i,j}] \right|^4 \right]}{\alpha^4}. \quad (\text{A.25})$$

We aim to prove Eq. (A.25) by showing that $c^2 E \left[\left| \tilde{h}_{i,j} - E[\tilde{h}_{i,j}] \right|^4 \right]$ converges as $c \rightarrow 0$. The rest of the proof of Lemma 2.3 is identical to Lemma 2.2 up to Eq. (A.7).

We denote $\varphi_1(z)$, $\varphi_2(z)$ and $\varphi_3(z)$ to be

$$\varphi_1(z) = \left(\frac{L-1}{L}\right)^z, \quad (\text{A.26})$$

$$\varphi_2(z) = \left(\frac{L-2}{L}\right)^z, \quad (\text{A.27})$$

$$\varphi_3(z) = \left(\frac{L-3}{L}\right)^z \quad (\text{A.28})$$

Using the inclusion–exclusion principle (which is analogous to Eq. (A.10)), we have¹⁸

$$\begin{aligned} E \left[\tilde{h}_{i,j}^m \tilde{h}_{i,j}^n \right] &= Pr(\tilde{h}_{i,j}^m \tilde{h}_{i,j}^n = 1) \\ &= 1 - Pr(\tilde{h}_{i,j}^m = 0) - Pr(\tilde{h}_{i,j}^n = 0) + Pr(\tilde{h}_{i,j}^m = 0 \wedge \tilde{h}_{i,j}^n = 0). \end{aligned} \quad (\text{A.30})$$

Using the inclusion–exclusion principle again, we derive

$$Pr(\tilde{h}_{i,j}^m = 0) = Pr(\tilde{h}_{i,j}^n = 0) = \varphi_1(l_i) + \varphi_1(l_j) - \varphi_1(l_i + l_j). \quad (\text{A.31})$$

and

$$\begin{aligned} Pr(\tilde{h}_{i,j}^m = 0 \wedge \tilde{h}_{i,j}^n = 0) &= Pr((\tilde{h}_i^m = 0 \vee \tilde{h}_j^m = 0) \wedge (\tilde{h}_i^n = 0 \vee \tilde{h}_j^n = 0)) \\ &= 2\varphi_1(l_i)(1 - \varphi_1(l_i))\varphi_1(l_j)(1 - \varphi_1(l_j)) \\ &\quad + \varphi_2(l_i) + \varphi_2(l_j) - \varphi_2(l_i)\varphi_2(l_j). \end{aligned} \quad (\text{A.32})$$

Substituting Eqs. (A.31) and (A.32) into Eq. (A.30), and taking the limit of c yields

$$\lim_{c \rightarrow 0} E \left[\tilde{h}_{i,j}^m \tilde{h}_{i,j}^n \right] = \left(1 - \exp\left(-\frac{k_m}{\mathcal{L}}\right) \right)^2 \left(1 - \exp\left(-\frac{k_n}{\mathcal{L}}\right) \right)^2. \quad (\text{A.33})$$

Similarly as in Eq. (A.33), we obtain the expectation of the cross product of three variables \tilde{h}^m, \tilde{h}^n and \tilde{h}^x as follows:

$$\begin{aligned} E \left[\tilde{h}_{i,j}^m \tilde{h}_{i,j}^n \tilde{h}_{i,j}^x \right] &= Pr(\tilde{h}_{i,j}^m \tilde{h}_{i,j}^n \tilde{h}_{i,j}^x = 1) \\ &= 1 - 3[\varphi_1(l_i) + \varphi_1(l_j) - \varphi_1(m+n)] \\ &\quad + 3[\varphi_1(l_i)(1 - \varphi_1(l_i))\varphi_1(l_j)(1 - \varphi_1(l_j)) + \varphi_2(l_i) + \varphi_2(l_j) - \varphi_2(l_i)\varphi_2(l_j)] \\ &\quad - [3(\varphi_1(l_i))^2(1 - \varphi_1(l_i))\varphi_1(l_j)(1 - \varphi_1(l_j))^2 + \varphi_1(l_i)(1 - \varphi_1(l_i))^2\varphi_1(l_j)^2(1 - \varphi_1(l_j))] \\ &\quad + 6\varphi_2(l_i)(1 - \varphi_1(l_i))\varphi_2(l_j)(1 - \varphi_1(l_j)) + \varphi_3(l_i) + \varphi_3(l_j) - \varphi_3(l_i)\varphi_3(l_j)]. \end{aligned} \quad (\text{A.34})$$

Taking the limit of c in Eq. (A.34) yields

$$\lim_{c \rightarrow 0} E \left[\tilde{h}_{i,j}^m \tilde{h}_{i,j}^n \tilde{h}_{i,j}^x \right] = \left(1 - \exp\left(-\frac{k_m}{\mathcal{L}}\right) \right)^3 \left(1 - \exp\left(-\frac{k_n}{\mathcal{L}}\right) \right)^3. \quad (\text{A.35})$$

¹⁸In this case, we use the inclusion–exclusion principle in the following form:

$$\left| \cup_{m=1}^M A_m \right| = \sum_{m=1}^M |A_m| - \sum_{1 \leq m < n \leq M} |A_m \cap A_n| + \sum_{1 \leq m < n < r \leq M} |A_m \cap A_n \cap A_r| + \dots + (-1)^{M+1} \left| \cap_{m=1}^M A_m \right|. \quad (\text{A.29})$$

We can repeat the same exercise as in Eq. (A.34) for the expectation of the cross product of four variables $\tilde{h}^m, \tilde{h}^n, \tilde{h}^x$ and \tilde{h}^y to obtain the following:

$$\lim_{c \rightarrow 0} E \left[\tilde{h}_{i,j}^m \tilde{h}_{i,j}^n \tilde{h}_{i,j}^x \tilde{h}_{i,j}^y \right] = \left(1 - \exp \left(-\frac{k_m}{\mathcal{L}} \right) \right)^4 \left(1 - \exp \left(-\frac{k_n}{\mathcal{L}} \right) \right)^4. \quad (\text{A.36})$$

Then, the rest of the proof is again identical to Lemma 2.2 to finish the proof. ■

Proof of Theorem 2.3 Let $n = 1/c$. With a slight modification of the notation in the main text, let H_n^i denote the set of distinct signals among those acquired by agent i for a fixed k^i and c , and let h_n^i denote the number of signals in H_n^i . Similarly, denote $H_n^{i,j}$ the set of distinct signals among the overlapping signals acquired by agent i and agent j for fixed k^i, k^j and c , and let $h_n^{i,j}$ denote the number of signals in $H_n^{i,j}$. Further, let \mathbf{L}_n be the set of signals in the urn when the cost of each draw is c ,¹⁹ and let L_n be the cardinality of \mathbf{L}_n . Then, let S_n^i denote the mean of the signals $s^1, s^2, \dots, s^{h_n^i}$ in H_n^i as follows:²⁰

$$S_n^i = \frac{1}{h_n^i} \sum_{m \in H_n^i} s^m = \theta + \sum_{m \in H_n^i} \epsilon^m,$$

and let $\tilde{\epsilon}_n^i$ denote $S_n^i - \theta$, that is,

$$\tilde{\epsilon}_n^i = \frac{1}{h_n^i} \sum_{m \in H_n^i} \epsilon^m. \quad (\text{A.37})$$

Outline of the proof. We will prove joint asymptotic normality of $\tilde{\epsilon}_n^i, \tilde{\epsilon}_n^j$ by showing that, as n goes to infinity,

$$a\tilde{\epsilon}_n^i + b\tilde{\epsilon}_n^j \xrightarrow{d} N \left(0, \frac{a^2}{\phi(k^i)} + \frac{b^2}{\phi(k^j)} + 2\frac{ab}{\tau\mathcal{L}} \right) \text{ for all } a, b \in \mathbb{R}^2 \quad (\text{A.38})$$

The plan of the proof is as follows. As a first step, starting from $\tilde{\epsilon}_n^i, \tilde{\epsilon}_n^j$, we construct two alternative random variables, $\hat{\epsilon}_n^i, \hat{\epsilon}_n^j$ say, whose distribution is unaffected by the randomness in h_n^i, h_n^j and $h_n^{i,j}$. As a second step, we use the CLT to prove asymptotic normality of $a\hat{\epsilon}_n^i + b\hat{\epsilon}_n^j$ as c goes to zero. As a third step, we prove that $a\tilde{\epsilon}_n^i + b\tilde{\epsilon}_n^j$ converges in probability to $a\hat{\epsilon}_n^i + b\hat{\epsilon}_n^j$ as c goes to zero. The fourth step combines the previous results and completes the proof.

First step. Let $\tilde{\mathbf{L}}_n$ be an independent copy of let \mathbf{L}_n , that is, a set of L_n signals of the form $\theta + \tilde{\epsilon}^m$, where each $\tilde{\epsilon}^m$ is independently and identically distributed to each ϵ^m in the signals in \mathbf{L}_n .

Let the random variable $z_n^{i,j}$ be defined as $z_n^{i,j} = h_n^{i,j} - \left\lceil E \left(h_n^{i,j} \right) \right\rceil$.²¹ Then, let the set $Z_n^{i,j}$ be defined as follows. If $z_n^{i,j} > 0$, let $Z_n^{i,j}$ be a set of $z_n^{i,j}$ random draws (without replacement) from $H_n^{i,j}$.

¹⁹In terms of the notation in the main text we have $h_n = \tilde{h}(k; \frac{1}{n})$ and $L_n = \lfloor n\mathcal{L} \rfloor$.

²⁰The signals and error terms s^m, ϵ^m should also have a n subscript to highlight that the distribution depends on n (i.e., c). We will omit such additional notation in the rest of the proof.

²¹ $\lceil x \rceil = \min\{z \in \mathbb{Z} | z \geq x\}$.

If $z_n^{i,j} < 0$, let $Z_n^{i,j}$ be a set of $\lfloor z_n^{i,j} \rfloor$ random draws (without replacement) from $\tilde{\mathbf{L}}_n$. If $z_n^{i,j} = 0$, let $Z_n^{i,j}$ be the null set. Then, let the set $\hat{H}_n^{i,j}$ be defined as follows:

$$\hat{H}_n^{i,j} = \begin{cases} H_n^{i,j} \setminus Z_n^{i,j} & \text{if } z_n^{i,j} > 0 \\ H_n^{i,j} \cup Z_n^{i,j} & \text{if } z_n^{i,j} \leq 0 \end{cases} .$$

By construction, the cardinality of $\hat{H}_n^{i,j}$ equals $\lceil E(h_n^{i,j}) \rceil$.

Let the random variable z_n^i be defined as $z_n^i = h_n^i - \lceil E(h_n^i) \rceil - z_n^{i,j}$. Then, let the set Z_n^i be defined as follows. If $z_n^i > 0$, let Z_n^i be a set of z_n^i random draws (without replacement) from $H_n^i \setminus H_n^{i,j}$. If $z_n^i < 0$, let Z_n^i be a set of $\lfloor z_n^i \rfloor$ random draws (without replacement) from $\tilde{\mathbf{L}}_n$. If $z_n^i = 0$, let Z_n^i be the null set. Then, let the set \hat{H}_n^i be defined as follows:

$$\hat{H}_n^i = \begin{cases} \left(H_n^i \setminus H_n^{i,j} \right) \setminus Z_n^i & \text{if } z_n^i > 0 \\ \left(H_n^i \setminus H_n^{i,j} \right) \cup Z_n^i & \text{if } z_n^i \leq 0 \end{cases} .$$

By construction, the cardinality of \hat{H}_n^i equals $\lceil E(h_n^i) \rceil - \lceil E(h_n^{i,j}) \rceil$. Define the random variable $\hat{\epsilon}_n^i$ as

$$\hat{\epsilon}_n^i = \frac{1}{\lceil E(h_n^i) \rceil} \left[\sum_{m \in \hat{H}_n^i} \epsilon^m + \sum_{m \in \hat{H}_n^{i,j}} \epsilon^m \right]. \quad (\text{A.39})$$

By construction, $\hat{\epsilon}_n^i$ is therefore the sample average of $\lceil E(h_n^i) \rceil$ i.i.d. error terms, while $\tilde{\epsilon}_n^i$ is the sample average of h_n^i i.i.d. error terms.

Finally, let the random variable $\tilde{\epsilon}_n^j$ be constructed in an equivalent manner to $\hat{\epsilon}_n^i$ but for agent j .

Second step. Let $r_n = \lceil E(h_n^i) \rceil + \lceil E(h_n^j) \rceil - \lceil E(h_n^{i,j}) \rceil$. By construction, $a\hat{\epsilon}_n^i + b\hat{\epsilon}_n^j$ can be written out as the sum of r_n independent terms as follows:

$$a\hat{\epsilon}_n^i + b\hat{\epsilon}_n^j = \sum_{k=1}^{r_n} X_{nk},$$

where a number $\lceil E(h_n^i) \rceil - \lceil E(h_n^{i,j}) \rceil$ of the X_{nk} terms are of the form $X_{nk} = \frac{a}{\lceil E(h_n^i) \rceil} \epsilon^k$, a number $\lceil E(h_n^j) \rceil - \lceil E(h_n^{i,j}) \rceil$ of the X_{nk} terms are of the form $X_{nk} = \frac{b}{\lceil E(h_n^j) \rceil} \epsilon^k$ and a number $\lceil E(h_n^{i,j}) \rceil$ of the X_{nk} terms are of the form $X_{nk} = \left(\frac{a}{\lceil E(h_n^i) \rceil} + \frac{b}{\lceil E(h_n^j) \rceil} \right) \epsilon^k$. Since $E(\epsilon^k) = 0$, then $E(X_{nk}) = 0$.

Letting V_n^2 denote the variance of $a\hat{\epsilon}_n^i + b\hat{\epsilon}_n^j$, we have

$$V_n^2 = \sum_{k=1}^{r_n} \text{Var}(X_{nk})$$

$$\begin{aligned}
&= \text{Var}(\epsilon^k) \left[\left(\lceil E(h_n^i) \rceil - \lceil E(h_n^{i,j}) \rceil \right) \left(\frac{a}{\lceil E(h_n^i) \rceil} \right)^2 + \left(\lceil E(h_n^j) \rceil - \lceil E(h_n^{i,j}) \rceil \right) \left(\frac{b}{\lceil E(h_n^j) \rceil} \right)^2 \right. \\
&\quad \left. + \lceil E(h_n^{i,j}) \rceil \left(\frac{a}{\lceil E(h_n^i) \rceil} + \frac{b}{\lceil E(h_n^j) \rceil} \right)^2 \right] \\
&= \text{Var}(\epsilon^k) \left[\frac{a^2}{\lceil E(h_n^i) \rceil} + \frac{b^2}{\lceil E(h_n^j) \rceil} + \frac{2ab}{\lceil E(h_n^i) \rceil \lceil E(h_n^j) \rceil} \lceil E(h_n^{i,j}) \rceil \right] \tag{A.40} \\
&= \frac{n}{\tau} \left[\frac{a^2}{n\mathcal{L} \left[1 - \left(1 - \frac{1}{n\mathcal{L}} \right)^{nk^i} \right] + g_i(n)} + \frac{b^2}{n\mathcal{L} \left[1 - \left(1 - \frac{1}{n\mathcal{L}} \right)^{nk^j} \right] + g_j(n)} + \frac{2ab}{n\mathcal{L} + g_{i,j}(n)} \right],
\end{aligned}$$

for some deterministic functions $g_i(c)$, $g_j(c)$ and $g_{i,j}(c)$ that all vanish as $n \rightarrow \infty$. Hence, we have

$$\lim_{n \rightarrow \infty} V_n^2 = \frac{a^2}{\phi(k^i)} + \frac{b^2}{\phi(k^j)} + 2 \frac{ab}{\tau \mathcal{L}}. \tag{A.41}$$

The Lindeberg condition requires that, for all $\delta > 0$,

$$\lim_{n \rightarrow \infty} \sum_{k=1}^{r_n} \frac{1}{V_n^2} E(X_{nk}^2 \mathbf{1}_{\{|X_{nk}| \geq \delta V_n\}}) = 0. \tag{A.42}$$

We can write

$$\sum_{k=1}^{r_n} \frac{1}{V_n^2} E(X_{nk}^2 \mathbf{1}_{\{|X_{nk}| \geq \delta V_n\}}) = \lambda_n^i + \lambda_n^j + \lambda_n^{i,j},$$

where

$$\begin{aligned}
\lambda_n^i &= \frac{\left(\lceil E(h_n^i) \rceil - \lceil E(h_n^{i,j}) \rceil \right)}{V_n^2} E \left(\left(\frac{a\epsilon^k}{\lceil E(h_n^i) \rceil} \right)^2 \mathbf{1}_{\left\{ \left| \frac{a\epsilon^k}{\lceil E(h_n^i) \rceil} \right| \geq \delta V_n \right\}} \right) \\
\lambda_n^j &= \frac{\left(\lceil E(h_n^j) \rceil - \lceil E(h_n^{i,j}) \rceil \right)}{V_n^2} E \left(\left(\frac{b\epsilon^k}{\lceil E(h_n^j) \rceil} \right)^2 \mathbf{1}_{\left\{ \left| \frac{b\epsilon^k}{\lceil E(h_n^j) \rceil} \right| \geq \delta V_n \right\}} \right) \\
\lambda_n^{i,j} &= \frac{\lceil E(h_n^{i,j}) \rceil}{V_n^2} E \left(\left[\left(\frac{a}{\lceil E(h_n^i) \rceil} + \frac{b}{\lceil E(h_n^j) \rceil} \right) \epsilon^k \right]^2 \mathbf{1}_{\left\{ \left| \left(\frac{a}{\lceil E(h_n^i) \rceil} + \frac{b}{\lceil E(h_n^j) \rceil} \right) \epsilon^k \right| \geq \delta V_n \right\}} \right).
\end{aligned}$$

Using the expression for V_n^2 in (A.40) and simplifying, we can write

$$\lambda_n^i = \alpha_n^i \beta_n^i,$$

where

$$\alpha_n^i = \left(1 - \frac{\lceil E(h_n^{i,j}) \rceil}{\lceil E(h_n^i) \rceil} \right) \frac{a^2}{\left[a^2 + b^2 \frac{\lceil E(h_n^i) \rceil}{\lceil E(h_n^j) \rceil} + 2ab \frac{\lceil E(h_n^{i,j}) \rceil}{\lceil E(h_n^j) \rceil} \right]},$$

and

$$\beta_n^i = E \left(\left(\frac{\epsilon^k}{\sqrt{\text{Var}(\epsilon^k)}} \right)^2 \mathbf{1}_{\left\{ \left| \frac{a\epsilon^k}{\lceil E(h_n^i) \rceil} \right| \geq \delta V_n \right\}} \right).$$

Furthermore, note that we can write (assuming $a \neq 0$)

$$\left| \frac{a\epsilon^k}{\lceil E(h_n^i) \rceil} \right| \geq \delta V_n \Leftrightarrow \left| \frac{\epsilon^k}{\sqrt{\text{Var}(\epsilon^k)}} \right| \geq \frac{\delta}{|a|} \sqrt{\frac{\lceil E(h_n^i) \rceil^2 V_n^2}{\text{Var}(\epsilon^k)}} \Leftrightarrow |y^k| \geq \gamma_n^i,$$

where we define

$$y^k = \frac{\epsilon^k}{\sqrt{\text{Var}(\epsilon^k)}}$$

and

$$\gamma_n^i = \frac{\delta}{|a|} \sqrt{a^2 \lceil E(h_n^i) \rceil + b^2 \frac{\lceil E(h_n^i) \rceil^2}{\lceil E(h_n^j) \rceil} + 2ab \frac{\lceil E(h_n^{i,j}) \rceil}{\lceil E(h_n^j) \rceil} \lceil E(h_n^i) \rceil}.$$

Hence, we can write

$$\lim_{n \rightarrow \infty} \lambda_n^i = \lim_{n \rightarrow \infty} \alpha_n^i \int_{|y^k| \geq \gamma_n^i} (y^k)^2 dP.$$

Note that $\lim_{n \rightarrow \infty} \gamma_n^i = \infty$ while the distribution of y^k is independent of n (y^k is a standardized version of the original signal error term ϵ^k in the urn), and therefore $\mathbb{P}[|y^k| \geq \gamma_n^i] \downarrow 0$ as $n \uparrow \infty$. Since α_n^i has a finite limit as $n \rightarrow \infty$, then $\lim_{n \rightarrow \infty} \lambda_n^i = 0$. Similar steps show that $\lim_{n \rightarrow \infty} \lambda_n^j = \lim_{n \rightarrow \infty} \lambda_n^{i,j} = 0$, so that the Lindeberg condition (A.42) is satisfied. Then, the Lindeberg-Feller Central Limit Theorem implies

$$\frac{a\widehat{\epsilon}_n^i + b\widehat{\epsilon}_n^j}{V_n} \xrightarrow{d} N(0, 1),$$

or, equivalently, that

$$a\widehat{\epsilon}_n^i + b\widehat{\epsilon}_n^j \xrightarrow{d} N \left(0, \frac{a^2}{\phi(k^i)} + \frac{b^2}{\phi(k^j)} + 2\frac{ab}{\tau\mathcal{L}} \right). \quad (\text{A.43})$$

Third step. Note that we can write $\tilde{\epsilon}_n^i$ in (A.37) as

$$\tilde{\epsilon}_n^i = \frac{[E(h_n^i)]}{h_n^i} \frac{1}{[E(h_n^i)]} \sum_{m \in H_n^i} \epsilon^m = \frac{[E(h_n^i)]}{h_n^i} \check{\epsilon}_n^i,$$

where we define

$$\check{\epsilon}_n^i = \frac{1}{[E(h_n^i)]} \sum_{m \in H_n^i} \epsilon^m. \quad (\text{A.44})$$

We will first prove that $\check{\epsilon}_n^i \xrightarrow{i.p.} \tilde{\epsilon}_n^i$. We need to prove

$$\lim_{n \rightarrow \infty} \text{Prob}(|\check{\epsilon}_n^i - \tilde{\epsilon}_n^i| > \alpha) = 0. \quad (\text{A.45})$$

By Chebyshev's inequality,

$$\text{Prob}(|\check{\epsilon}_n^i - \tilde{\epsilon}_n^i| > \alpha) \leq \frac{\text{Var}(\check{\epsilon}_n^i - \tilde{\epsilon}_n^i)}{\alpha^2}. \quad (\text{A.46})$$

By the variance decomposition formula,

$$\text{Var}(\check{\epsilon}_n^i - \tilde{\epsilon}_n^i) = E[\text{Var}(\check{\epsilon}_n^i - \tilde{\epsilon}_n^i | h_n^i, h_n^{i,j})] + \text{Var}[E(\check{\epsilon}_n^i - \tilde{\epsilon}_n^i | h_n^i, h_n^{i,j})].$$

Since $E(\check{\epsilon}_n^i - \tilde{\epsilon}_n^i | h_n^i, h_n^{i,j}) = 0$, we are left with

$$E[\text{Var}(\check{\epsilon}_n^i - \tilde{\epsilon}_n^i | h_n^i, h_n^{i,j})] = \frac{1}{[E(h_n^i)]^2} E \left[\text{Var} \left(\sum_{m \in H_n^i \setminus H_n^{i,j}} \epsilon^m - \sum_{m \in \hat{H}_n^i} \epsilon^m + \sum_{m \in H_n^{i,j}} \epsilon^m - \sum_{m \in \hat{H}_n^{i,j}} \epsilon^m \right) \right].$$

Note that, by construction, $H_n^{i,j}$ and $\hat{H}_n^{i,j}$ differ by exactly $|z_n^{i,j}|$ elements, while $H_n^i \setminus H_n^{i,j}$ and \hat{H}_n^i differ by exactly $|z_n^i|$ elements. Hence, we can write the last expression as

$$\begin{aligned} E[\text{Var}(\check{\epsilon}_n^i - \tilde{\epsilon}_n^i | h_n^i, h_n^{i,j})] &= \frac{\text{Var}(\epsilon^m)}{[E(h_n^i)]^2} E[|z_n^i| + |z_n^{i,j}|] \\ &= \frac{\text{Var}(\epsilon^m)}{[E(h_n^i)]^2} E[|h_n^i - [E(h_n^i)] - z_n^{i,j}| + |z_n^{i,j}|] \\ &\leq \frac{\text{Var}(\epsilon^m)}{[E(h_n^i)]^2} E[|h_n^i - [E(h_n^i)]| + 2|z_n^{i,j}|] \\ &= \frac{\text{Var}(\epsilon^m)}{[E(h_n^i)]^2} E[|h_n^i - [E(h_n^i)]| + 2|h_n^{i,j} - [E(h_n^{i,j})]|] \end{aligned}$$

$$\begin{aligned}
&= \frac{\text{Var}(\epsilon^m)}{[E(h_n^i)]} \left(E \left[\left| \frac{h_n^i}{[E(h_n^i)]} - 1 \right| \right] + 2 \frac{[E(h_n^{i,j})]}{[E(h_n^i)]} E \left[\left| \frac{h_n^{i,j}}{[E(h_n^{i,j})]} - 1 \right| \right] \right) \\
&= \frac{\text{Var}(\epsilon^m)}{[E(h_n^i)]} \left(E [|w_n^i - 1|] + 2 \frac{[E(h_n^{i,j})]}{[E(h_n^i)]} E [|w_n^{i,j} - 1|] \right)
\end{aligned}$$

where the second line follows from the definition of z_n^i , the third line follows by the triangle inequality, the fourth line follows from the definition of $z_n^{i,j}$, the fifth line from rearranging terms and the last line uses the following definitions:

$$w_n^i = \frac{h_n^i}{E(h_n^i) + g_i(n)}; \quad w_n^{i,j} = \frac{h_n^{i,j}}{E(h_n^{i,j}) + g_{i,j}(n)},$$

for two deterministic functions $g_i(n)$ and $g_{i,j}(n)$ that converge to zero as $n \rightarrow \infty$.

By Lemma 2.2 in the paper, $\frac{1}{n}h_n^i \xrightarrow{a.s.} \frac{1}{n}E(h_n^i)$ and therefore $w_n^i \xrightarrow{a.s.} 1$. Since $|w_n^i|$ is bounded from above by the constant $(1 - e^{-k^i/\mathcal{L}})^{-1}$, the dominated convergence theorem implies that w_n^i converges in the L^1 norm, that is,

$$\lim_{n \rightarrow \infty} E [|w_n^i - 1|] = 0.$$

By Lemma 2.3 in the paper, $\frac{1}{n}h_n^{i,j} \xrightarrow{a.s.} \frac{1}{n}E(h_n^{i,j})$ and therefore $w_n^{i,j} \xrightarrow{a.s.} 1$. Since $|w_n^{i,j}|$ is bounded from above by the constant $\left[(1 - e^{-k^i/\mathcal{L}}) (1 - e^{-k^j/\mathcal{L}}) \right]^{-1}$, the dominated convergence theorem implies that $w_n^{i,j}$ converges in the L^1 norm, that is,

$$\lim_{n \rightarrow \infty} E [|w_n^{i,j} - 1|] = 0.$$

Since $\frac{\text{Var}(\epsilon^m)}{[E(h_n^i)]}$ and $\frac{[E(h_n^{i,j})]}{[E(h_n^i)]}$ have finite limits as $n \uparrow \infty$, we have shown that

$$\lim_{n \rightarrow \infty} \text{Var}(\tilde{\epsilon}_n^i - \tilde{\epsilon}_n^i) = 0,$$

which completes the proof of (A.45).

Finally, since $\tilde{\epsilon}_n^i \xrightarrow{i.p.} \hat{\epsilon}_n^i$ and $\frac{[E(h_n^i)]}{h_n^i} \xrightarrow{i.p.} 1$ (which is implied by $\frac{1}{n}h_n^i \xrightarrow{a.s.} \frac{1}{n}E(h_n^i)$ and the continuous mapping theorem) and $\tilde{\epsilon}_n^i = \frac{[E(h_n^i)]}{h_n^i} \tilde{\epsilon}_n^i$, then $\tilde{\epsilon}_n^i \xrightarrow{i.p.} \hat{\epsilon}_n^i$. An identical proof shows that $\tilde{\epsilon}_n^j \xrightarrow{i.p.} \hat{\epsilon}_n^j$, and therefore

$$a\tilde{\epsilon}_n^i + b\tilde{\epsilon}_n^j \xrightarrow{i.p.} a\hat{\epsilon}_n^i + b\hat{\epsilon}_n^j. \quad (\text{A.47})$$

Fourth step. By (A.43) and (A.47), Theorem 2.7 in Van der Vaart (2000) implies that (A.38) holds. Hence, by Theorem 29.4 in Billingley (1995), $\tilde{\epsilon}_n^i$ and $\tilde{\epsilon}_n^j$ are jointly normally distributed. ■

Proof of Corollary 2.1: Notice that

$$Var(\mu) = \frac{1}{I^2} \sum_{i=1}^I Var(\epsilon_i) + \frac{1}{I^2} \sum_{i=1}^I \sum_{j \neq i}^I Cov(\epsilon_i, \epsilon_j) \quad (\text{A.48})$$

$$= \frac{1}{I^2} \sum_{i=1}^I \phi^{-1}(k_i) + \frac{I-1}{I} \frac{1}{\tau \mathcal{L}}, \quad (\text{A.49})$$

and

$$Cov(\epsilon_i, \mu) = \frac{1}{I} \left(Var(\epsilon_i) + \sum_{j \neq i} Cov(\epsilon_i, \epsilon_j) \right) \quad (\text{A.50})$$

$$= \frac{1}{I} \phi^{-1}(k_i) + \frac{I-1}{I} \frac{1}{\tau \mathcal{L}}. \quad (\text{A.51})$$

Therefore, we have

$$Cov(\eta_i, \mu) = Cov(\epsilon_i, \mu) - Var(\mu) = \frac{1}{I^2} \sum_{j=1}^I \phi^{-1}(k_j) - \frac{1}{I} \phi^{-1}(k_i), \quad (\text{A.52})$$

and

$$Var(\eta_i) = Var(\epsilon_i - \mu) = Var(\epsilon_i) - 2Cov(\epsilon_i, \mu) + Var(\mu) \quad (\text{A.53})$$

$$= \left(1 - \frac{2}{I}\right) \phi^{-1}(k_i) - \frac{I-1}{I} \frac{1}{\tau \mathcal{L}} + \frac{1}{I^2} \sum_{j=1}^I \phi^{-1}(k_j), \quad (\text{A.54})$$

and

$$Cov(\eta_i, \eta_j) = Cov(\epsilon_i - \mu, \epsilon_j - \mu) = Cov(\epsilon_i, \epsilon_j) - Cov(\epsilon_i, \mu) - Cov(\epsilon_j, \mu) + Var(\mu) \quad (\text{A.55})$$

$$= \frac{1}{\tau \mathcal{L}} - \frac{1}{I} \phi^{-1}(k_i) - \frac{1}{I} \phi^{-1}(k_j) - \frac{I-1}{I} \frac{1}{\tau \mathcal{L}} + \frac{1}{I^2} \sum_{i=1}^I \phi^{-1}(k_i). \quad (\text{A.56})$$

Therefore, we have the following results in the limit where I tends to infinity:

$$\lim_{I \rightarrow \infty} Var(\eta_i) = \frac{1}{\phi(k_i)} - \frac{1}{\tau \mathcal{L}}, \quad \text{for all } i \in \mathbf{I} \quad (\text{A.57})$$

$$\lim_{I \rightarrow \infty} Cov(\eta_i, \mu) = 0, \quad \text{for all } i \in \mathbf{I} \quad (\text{A.58})$$

$$\lim_{I \rightarrow \infty} Cov(\eta_i, \eta_j) = 0, \text{ for all } i, j \in \mathbf{I} \quad (\text{A.59})$$

$$\lim_{I \rightarrow \infty} Var(\mu) = \frac{1}{\tau \mathcal{L}}. \quad (\text{A.60})$$

Using the definition of $\phi(k_i)$ in Theorem 2.1 it is immediate to rearrange the r.h.s. of Eq. (A.57) as in the statement of Corollary 2.1. ■

Appendix B

Ex-ante utility. Assuming all agents play some strategy $(\hat{k}, \hat{\gamma})$, the average action equals $\bar{a} = \hat{\gamma}^0 + \Sigma_j \hat{\gamma}^j (\theta + \mu_j)$. Agent i 's ex-ante utility from playing strategy (k_i, γ_i) is

$$E(u_i) = -(1 - \delta) E(\theta - a^i)^2 - \delta E(\bar{a} - a^i)^2,$$

where

$$\begin{aligned} E(\theta - a_i)^2 &= E\left(\theta - \gamma_i^0 - \Sigma_j \gamma_i^j S_j^i\right)^2 \\ &= E\left((\theta - \bar{\theta})\left(1 - \Sigma_j \gamma_i^j\right) + \bar{\theta}\left(1 - \Sigma_j \gamma_i^j\right) - \gamma_i^0 - \Sigma_j \gamma_i^j \epsilon_j^i\right)^2 \\ &= \left(1 - \Sigma_j \gamma_i^j\right)^2 \tau_\theta^{-1} + \left(\bar{\theta}\left(1 - \Sigma_j \gamma_i^j\right) - \gamma_i^0\right)^2 + \Sigma_j \left(\gamma_i^j\right)^2 \phi^j \left(k_i^j\right)^{-1} \end{aligned}$$

and

$$\begin{aligned} E(\bar{a} - a_i)^2 &= E\left(\hat{\gamma}^0 + \Sigma_j \hat{\gamma}^j (\theta + \mu_j) - \gamma_i^0 - \Sigma_j \gamma_i^j S_j^i\right)^2 \\ &= E\left(\hat{\gamma}^0 - \gamma_i^0 + \bar{\theta}\left(\Sigma_j \hat{\gamma}^j - \Sigma_j \gamma_i^j\right) + \left(\Sigma_j \hat{\gamma}^j - \Sigma_j \gamma_i^j\right)(\theta - \bar{\theta}) + \Sigma_j \left(\hat{\gamma}^j - \gamma_i^j\right) \mu_j - \Sigma_j \gamma_i^j \eta_j^i\right)^2 \\ &= \left(\hat{\gamma}^0 - \gamma_i^0 + \bar{\theta}\left(\Sigma_j \hat{\gamma}^j - \Sigma_j \gamma_i^j\right)\right)^2 + \left(\Sigma_j \hat{\gamma}^j - \Sigma_j \gamma_i^j\right)^2 \tau_\theta^{-1} + \\ &+ \Sigma_j \left(\hat{\gamma}^j - \gamma_i^j\right)^2 \left(\tau^j \mathcal{L}^j\right)^{-1} + \Sigma_j \left(\gamma_i^j\right)^2 \left(\phi^j \left(k_i^j\right)^{-1} - \left(\tau^j \mathcal{L}^j\right)^{-1}\right). \end{aligned}$$

It is immediate to rearrange terms as in Eq. (33), where we define

$$L_1(k_i, \gamma_i) = (1 - \delta) \left(\tau_\theta^{-1} \left(1 - \Sigma_{j=1}^J \gamma_i^j\right)^2 + \left(\bar{\theta}\left(1 - \Sigma_{j=1}^J \gamma_i^j\right) - \gamma_i^0\right)^2 \right) + \Sigma_{j=1}^J \left(\gamma_i^j\right)^2 \left(\phi^j \left(k_i^j\right)^{-1} - \frac{\delta}{\tau^j \mathcal{L}^j}\right), \quad (\text{B.1})$$

and

$$L_2(\gamma_i, \hat{\gamma}) = \delta \left[\tau_\theta^{-1} \left(\Sigma_{j=1}^J \gamma_i^j - \Sigma_{j=1}^J \hat{\gamma}^j\right)^2 + \Sigma_{j=1}^J \left(\gamma_i^j - \hat{\gamma}^j\right)^2 \frac{1}{\tau^j \mathcal{L}^j} + \left(\bar{\theta}\left(\Sigma_{j=1}^J \gamma_i^j - \Sigma_{j=1}^J \hat{\gamma}^j\right) + \hat{\gamma}^0 - \gamma_i^0\right)^2 \right]. \quad (\text{B.2})$$

We remark that Eq. (B.2) implies

$$L_2(\gamma_i, \hat{\gamma}) > 0 \text{ for } \gamma_i \neq \hat{\gamma}; \quad L_2(\hat{\gamma}, \hat{\gamma}) = 0; \quad \frac{\partial}{\partial \gamma_i} L_2(\hat{\gamma}, \hat{\gamma}) = 0. \quad (\text{B.3})$$

Lemma B.1. A strategy $(\hat{k}, \hat{\gamma})$ is a SBNE only if: (i) $\hat{\gamma}$ satisfies

$$\hat{\gamma}^j = \tilde{\gamma}^j(\hat{k}) = \begin{cases} \bar{\theta} \left(1 - \sum_{j=1}^J \hat{\gamma}^j\right) & \text{for } j = 0 \\ \frac{(1-\delta)g_j(\hat{k}^j)}{\tau_\theta + (1-\delta)\sum_{n=1}^J g_n(\hat{k}^n)}, & \text{for } j = 1, \dots, J \end{cases} \quad (\text{B.4})$$

where

$$g_j(k) = \phi^j(k) [1 - \delta + \delta \exp(-k^j/\mathcal{L}^j)]^{-1}, \quad (\text{B.5})$$

and (ii) \hat{k} satisfies $\sum_{j=1}^J \hat{k}^j = K$.

(iii) In a payoff maximizing equilibrium, the equilibrium resource allocation solves

$$k^* \in \arg \max_{k_i \in \Delta} \sum_{j=1}^J g_j(k_j) \quad \text{s.t.} \quad \sum_{j=1}^J k_i^j = K. \quad (\text{B.6})$$

Proof of part (i). Let $\tilde{\gamma}(k_i) \in \arg \min_{(\gamma_i)} L_1(k_i, \gamma_i)$. Fixing k_i , it is immediate to verify that $L_1(k_i, \gamma_i)$ is strictly convex in γ_i for all $\delta \in [0, 1]$. Differentiating $L_1(k_i, \gamma_i)$ with respect to γ_i and solving the system of first-order conditions for γ_i gives

$$\begin{aligned} \tilde{\gamma}_0(k_i) &= \bar{\theta} (1 - \sum_{j=1}^J \tilde{\gamma}^j(k_i)), \\ \tilde{\gamma}^j(k_i) &= \frac{(1-\delta) \tau_\theta^{-1} \phi^j(k_i^j) [1 - \delta + \delta \exp(-k^j/\mathcal{L}^j)]^{-1}}{1 + (1-\delta) \tau_\theta^{-1} \sum_{n=1}^J \phi_n(k_i^n) [1 - \delta + \delta \exp(-k^j/\mathcal{L}^j)]^{-1}} \quad \text{for } j = 1, \dots, J. \end{aligned}$$

Note that the expression for $\hat{\gamma}^j$ in Eq. (B.4) equals $\tilde{\gamma}^j(\hat{k})$. Then, assume $(\hat{k}, \hat{\gamma})$ is a SBNE and $\hat{\gamma}^j \neq \tilde{\gamma}^j(\hat{k})$ for some j . Consider an agent deviating locally from $\hat{\gamma}^j$. First-order effects of deviations of γ_i^j from $\hat{\gamma}^j$ are zero for L_2 (see Eq. (B.3)). Strict convexity of L_1 in γ_i implies that, if $\hat{\gamma}^j \neq \tilde{\gamma}^j(\hat{k})$, then $\frac{\partial}{\partial \gamma_i} L_1(\hat{k}, \hat{\gamma}) \neq 0$. Therefore, there is a profitable deviation, contradicting $(\hat{k}, \hat{\gamma})$ being a SBNE. ■

Proof of part (ii). Assume $(\hat{k}, \hat{\gamma})$ is a SBNE and $\sum_{j=1}^J \hat{k}^j < K$. By part (i), it has to be that $\hat{\gamma} = \tilde{\gamma}(\hat{k})$. Substituting $\tilde{\gamma}(k_i)$ for γ_i into $L_1(k_i, \gamma_i)$, we obtain

$$\tilde{L}_1(k_i) = L_1(k_i, \tilde{\gamma}(k_i)) = \frac{(1-\delta) \tau_\theta^{-1}}{1 + (1-\delta) \tau_\theta^{-1} \sum_{j=1}^J g_j(k_i^j)}. \quad (\text{B.7})$$

Inspection of the functions g_j in Eq. (B.5) reveals that each g_j is strictly increasing for $\delta \in [0, 1]$. Then, assume $(\hat{k}, \tilde{\gamma}(\hat{k}))$ is a SBNE and $\sum_{j=1}^J \hat{k}^j < K$. Then, consider agent i deviating locally from \hat{k}

by increasing marginally k_i^j from \hat{k}_j . The deviation is feasible, it decreases L_1 and it has no first-order effect on L_2 (see Eq. (B.3)). Then, because g_j is strictly increasing we have $\partial \tilde{L}_1(k_i) / \partial k_i^j \Big|_{k_i^j = \hat{k}_j} > 0$. Therefore, there exists a profitable deviation, contradicting $(\hat{k}, \tilde{\gamma}(\hat{k}))$ being a SBNE. ■

Proof of part (iii). Follows trivially by part (ii) and the fact that $\tilde{L}_1(k_i)$ in Eq. (B.7) is strictly decreasing in $\sum_{j=1}^J g_j(k_i^j)$. ■

Proof of Proposition 3.1 . By Lemma B.1 and Eq. (B.7), finding k^* that minimizes L_1 is equivalent to the following problem. Inspection of the functions g_j in Eq. (B.5) reveals that each g_j is strictly concave for $\delta \in [0, 1/2)$. Therefore, we can convert the problem in Eq. (B.6) to the following dual problem:

$$\min_{\lambda} \lambda K - \sum_{j=1}^J g_j^*(\lambda),$$

where $g_j^*(\lambda)$ is the conjugate function of $g_j(k^j)$ such that

$$g_j^*(\lambda) = \min_{k^j \geq 0} \left(\lambda k^j - \phi^j(k^j) \frac{\exp(k^j / \mathcal{L}^j)}{\exp(k^j / \mathcal{L}^j) (1 - \delta) + \delta} \right).$$

The F.O.C. gives

$$\lambda - \frac{\tau^j \exp(k^j / \mathcal{L}^j)}{[(1 - \delta) \exp(k^j / \mathcal{L}^j) + \delta]^2} = 0, \quad (\text{B.8})$$

which has a strictly positive solution for k^j if and only if $0 < \lambda < \tau^j$, in which case it is immediate to verify that k^j is as in Eq. (37). Finally, λ can be obtained by solving the following equation:

$$\sum_{j=1}^J \hat{k}^j(\lambda) = K. \quad (\text{B.9})$$

Notice that l.h.s. is zero when $\lambda = \infty$ and infinity when $\lambda = 0$ and each $\hat{k}^j(\lambda)$ is strictly decreasing in λ for $0 < \lambda < \tau^j$. Therefore, there exists a unique $\lambda > 0$ that solves for Eq. (B.9) because l.h.s. is continuous and monotone decreasing in λ .

We now prove the statements in the proposition regarding uniqueness of equilibrium. By Lemma B.1, in an equilibrium $\hat{\gamma}$ must satisfy $\hat{\gamma} = \tilde{\gamma}(\hat{k})$. Therefore, the problem is reduced to whether the equilibrium resource allocation \hat{k} is unique. In an equilibrium, local deviations in (k_i, γ_i) starting from $(\hat{k}, \tilde{\gamma}(\hat{k}))$ must not provide a profitable deviation to an agent. Since an agent's local deviation from a symmetric strategy profile has no first-order effect on $L_2(\gamma_i, \hat{\gamma})$ (see Eq.(B.3)), an equilibrium resource allocation must be either a local minimum or a critical point of $\tilde{L}_1(k_i)$ in Eq. (B.7). Equivalently, an equilibrium resource allocation must be either a local maximum or a critical point of $G(k) = \sum_{j=1}^J g_j(k^j)$. For $\delta \in [0, 1/2)$ the resource allocation in Eq. (37) is the unique maximizer of $G(k)$. Since $G(k)$ is strictly concave in k_i for $\delta \in [0, 1/2)$, the equilibrium resource allocation in Eq. (37)

is unique. This completes the proof of part (i) of the proposition. For $\delta \in [1/2, 1]$, $G(k)$ fails to be strictly concave. Then, a global maximizer of $G(k)$ is clearly an equilibrium, but a critical point and a local maximum of $G(k)$ can also be an equilibrium because the loss term $L_2(\gamma_i, \hat{\gamma}) > 0$ for $\gamma_i \neq \hat{\gamma}$. This completes the proof of part (ii) of the proposition. ■

Proof of Proposition 3.2-(i). We want to prove that $\hat{k}^A = K, \hat{k}^B = 0$ is an equilibrium. By Lemma B.1 and Eqs. (B.4), it must be $\hat{\gamma}^0 = (1 - \hat{\gamma}^A)\bar{\theta}$, $\hat{\gamma}^A = \frac{(1-\delta)\tau^A K}{\tau\theta + (1-\delta)\tau^A K}$ and $\hat{\gamma}^B = 0$. Then, consider the corresponding problem in Eq. (34) using these values for $(\hat{k}, \hat{\gamma})$. Denote $k(\alpha_i) = (k^A(\alpha_i), k^B(\alpha_i))$ where $k^A(\alpha_i) = (1 - \alpha_i)K$ and $k^B = \alpha_i K$. Fixing $\alpha_i \in [0, 1]$ and letting $\gamma_i(\alpha_i) = \arg \min_{\gamma_i} L_1(k(\alpha_i), \gamma_i) + L_2(\gamma_i, \hat{\gamma})$ we obtain

$$\begin{aligned}\hat{\gamma}_i^0(a_i) &= (1 - \gamma_i^A(a_i) - \gamma_i^B(a_i))\bar{\theta} \\ \gamma_i^A(a_i) &= \frac{(1 - \delta)(\phi^A(K) + \tau\theta)}{(\phi^A(K)(1 - \delta) + \tau\theta)(\tau\theta + \phi^A((1 - \alpha_i)K) + \phi^B(\alpha_i K))} \phi^A((1 - \alpha_i)K) \\ \gamma_i^B(a_i) &= \frac{(1 - \delta)(\phi^A(K) + \tau\theta)}{(\phi^A(K)(1 - \delta) + \tau\theta)(\tau\theta + \phi^A((1 - \alpha_i)K) + \phi^B(\alpha_i K))} \phi^B(\alpha_i K).\end{aligned}$$

Substituting these optimal values for γ_i into the problem leaves

$$\begin{aligned}L_3(\alpha_i) &= L_1(k(\alpha_i), \gamma_i(\alpha_i)) + L_2(\gamma_i(\alpha_i), \hat{\gamma}) \\ &= \frac{(1 - \delta)\tau\theta(\phi^A(K)^2(1 - \delta)\tau\theta^{-1} + (2 - \delta(1 + \alpha_i))\phi^A(K) + \tau\theta + \delta\phi^B(\alpha_i K))}{(\phi^A(K)(1 - \delta) + \tau\theta)^2(\tau\theta + \phi^A((1 - \alpha_i)K) + \phi^B(\alpha_i K))}.\end{aligned}$$

Straightforward algebra shows that $L_3(\alpha_i)$ is strictly increasing in α_i if $\tau^A > \tau^B$. ■

Proof of Proposition 3.2-(ii). By Proposition 3.2-(i), an equilibrium \hat{k} must be a local maximum or a critical point of $G(k) = \sum_{j=1}^J g_j(k_j^j)$. Equivalently $\alpha = 1$ must be a local maximum or a critical point of $G_\alpha(\alpha)$, where we define

$$G_\alpha(\alpha) = g_A((1 - \alpha)K) + g_B(\alpha K). \quad (\text{B.10})$$

That is, for $\alpha = 1$ to be an equilibrium it must be

$$\frac{d}{d\alpha} G_\alpha(1) \geq 0 \Leftrightarrow e^{K/\mathcal{L}^B} \geq \frac{\tau^A}{\tau^B} \left(e^{K/\mathcal{L}^B} (1 - \delta) + \delta \right)^2. \quad (\text{B.11})$$

Letting $\bar{\mathcal{L}}_N = \frac{K}{\log(\tau^A/\tau^B)}$, it is immediate to verify that the necessary condition in Eq. (B.11) is satisfied only if $\mathcal{L}^B \leq \bar{\mathcal{L}}_N$. ■

Proof of Proposition 3.2-(iii). Define

$$\tilde{\delta}(\mathcal{L}^B) = \frac{e^{K/\mathcal{L}^B}}{1 + e^{K/\mathcal{L}^B}}.$$

It is immediate to verify that $G_\alpha(\alpha)$ in Eq. (B.10) is strictly convex in α for all $\alpha \in [0, 1]$ if $\delta \in (\tilde{\delta}(\mathcal{L}^B), 1]$. Letting $\alpha^* = \arg \max_{\alpha \in [0, 1]} G_\alpha(\alpha)$, strict convexity of $G_\alpha(\alpha)$ implies $\alpha^* \in \{0, 1\}$. Therefore, $\alpha = 1$ is the unique payoff maximizing SBNE if

$$G_\alpha(1) > G_\alpha(0) \Leftrightarrow \frac{\tau^A}{\tau^B} \frac{K}{\mathcal{L}^B} < \frac{e^{K/\mathcal{L}^B} - 1}{e^{K/\mathcal{L}^B} (1 - \delta) + \delta} \quad (\text{B.12})$$

Notice that the r.h.s. of the second inequality in Eq. (B.12) is increasing in δ . As $\delta \rightarrow 1$, Eq. (B.12) holds if $\mathcal{L}^B < \bar{\mathcal{L}}_S$, where $\bar{\mathcal{L}}_S \in (0, \infty)$ solves

$$\frac{\tau^A}{\tau^B} \frac{K}{\bar{\mathcal{L}}_S} = e^{K/\bar{\mathcal{L}}_S} - 1.$$

Hence, for all $\mathcal{L}^B < \bar{\mathcal{L}}_S$, Eq. (B.12) holds if $\delta \in (\check{\delta}(\mathcal{L}^B), 1]$, where we define

$$\check{\delta}(\mathcal{L}^B) = \frac{e^{K/\mathcal{L}^B}}{e^{K/\mathcal{L}^B} - 1} - \frac{\mathcal{L}^B \tau^B}{K \tau^A}.$$

Combining these results, $\alpha = 1$ is the unique payoff maximizing SBNE if $\mathcal{L}^B < \bar{\mathcal{L}}_S$ and $\delta \in (\delta_S(\mathcal{L}^B), 1]$, where $\delta_S(\mathcal{L}^B) = \max\{\tilde{\delta}(\mathcal{L}^B), \check{\delta}(\mathcal{L}^B)\}$. ■

Proof of Corollary 3.1 For all for all $\mathcal{L}^B \in (\infty, \bar{\mathcal{L}}_S]$, we have $\tilde{\delta}(\mathcal{L}^B) < 1$ and $\check{\delta}(\mathcal{L}^B) \leq 1$, where the equality holds if and only if $\mathcal{L}^B = \bar{\mathcal{L}}_S$. Then, then, we have $\delta_S(\bar{\mathcal{L}}_S) = 1$ and $\delta_S(\mathcal{L}^B) < 1$ for all $\mathcal{L}^B < \bar{\mathcal{L}}_S$. The statement in the corollary follows by continuity of $\delta_S(\mathcal{L}^B)$, which in turn is implied by continuity of $\tilde{\delta}(\mathcal{L}^B)$ and $\check{\delta}(\mathcal{L}^B)$. ■

Appendix C

There is a standard formula which computes the certainty equivalence of expected utilities in case of CARA utilities. (For example, see Dow and Rahi (2003))

Lemma C.2. *Suppose A is a symmetric $m \times m$ matrix, b is an m -vector, d is a scalar, and w is an m -dimensional normal variate: $w \sim N(0, \Sigma)$, Σ positive definite. Then, we can find the following certainty equivalence of expected utilities if $(I - 2\Sigma A)$ is positive definite*

$$E \left[\exp(w^\top A w + b^\top w + d) \right] = |I - 2\Sigma A|^{-\frac{1}{2}} \exp \left[\frac{1}{2} b^\top (I - 2\Sigma A)^{-1} \Sigma b + d \right]. \quad (\text{C.1})$$

Proof of Proposition 4.1. For notational convenience, we denote $S = (S^1, S^2, \dots, S^N)$ to be the vector of all the signals acquired by the trader. The value function for the trader's optimal portfolio choice problem conditional on the acquired signals is given by

$$V(w_0; S) = \max_{x^1, x^2, \dots, x^N} E \left[-\exp \left(-\gamma \left(w_0 + \sum_{j=1}^N (\theta^j - p^j) x^j \right) \right) \middle| S \right] \quad (\text{C.2})$$

where x^j is the unit of holdings of asset j . Then, the demand for each asset j is given by the standard CARA-Gaussian demand:

$$x^j = \frac{E[\theta | S^j] - p^j}{\gamma \text{Var}[\theta | S^j]}. \quad (\text{C.3})$$

By Lemma C.2, the expected utility can be obtained from Eqs. (C.2) and (C.3) as follows:

$$E[V(w_0; S)] = - \prod_{j=1}^N \sqrt{\frac{\tau_\theta^j}{\tau_\theta^j + \phi^j(k^j)}} \exp \left(-\gamma w_0 - \frac{1}{2} \sum_{j=1}^N \tau_\theta^j p^{j^2} \right). \quad (\text{C.4})$$

Maximizing Eq. (C.4) under the resource constraint in Eq. (38) is equivalent to the following optimal resource allocation problem:²²

$$\max_{\sum_{j=1}^N k^j = K} \sum_{j=1}^N G_j(k^j) \quad (\text{C.5})$$

where $G_j(k^j) = \log \left(\tau_\theta^j + \phi^j(k^j) \right)$.

²²Notice that other components in Eq. (C.4) are unaffected by the choice of resource allocations than $\prod_{j=1}^N \sqrt{\frac{\tau_\theta^j}{\tau_\theta^j + \phi^j(k^j)}}$. Using a log-transformation, we get (C.5).

Notice that each $G_j(k^j)$ is concave in k^j because $\phi^j(k^j)$ is concave. Therefore, we can convert this problem in Eq. (C.5) to the following dual problem:

$$\min_{\lambda} \lambda K - \sum_{j=1}^N G_j^*(\lambda) \quad (\text{C.6})$$

where $G_j^*(\lambda)$ is the conjugate function of $G_j(k^j)$ such that

$$G_j^*(\lambda) = \min_{k^j \geq 0} \left(\lambda k^j - \log \left(\tau_{\theta}^j + \phi^j(k^j) \right) \right) \quad (\text{C.7})$$

For all each asset j , the optimal allocation k^j given λ is

$$k^j(\lambda) = \begin{cases} \mathcal{L}^j \log \left(\frac{\frac{\hat{\tau}^j}{\lambda} + \hat{\tau}^j \mathcal{L}^j}{1 + \hat{\tau}^j \mathcal{L}^j} \right) & \text{if } 0 < \lambda < \hat{\tau}^j \\ 0 & \text{if } \lambda \geq \hat{\tau}^j \end{cases} \quad (\text{C.8})$$

Finally, λ can be obtained by solving the following equation:

$$\sum_{j=1}^N k^j(\lambda) = K. \quad (\text{C.9})$$

Notice that l.h.s. is zero when $\lambda = \infty$ and infinity when $\lambda = 0$. Therefore, it is easily verified that there exists a unique solution for Eq. (C.9) because l.h.s. is continuous and monotone decreasing in λ .

Now, we turn to the proof that λ decreases in K . Using the implicit function theorem, we get

$$\frac{\partial(\sum_{j=1}^N k^j(\lambda) - K)}{\partial K} dK + \frac{\partial(\sum_{j=1}^N k^j(\lambda) - K)}{\partial \lambda} d\lambda = 0, \quad (\text{C.10})$$

which implies that

$$\frac{d\lambda}{dK} = - \frac{1}{\sum_{j \in \mathbb{J}} \mathcal{L}^j \left(\frac{\frac{1}{\lambda^2}}{\frac{1}{\lambda} + \mathcal{L}^j} \right)} < 0. \quad (\text{C.11})$$

We can similarly prove that λ increases in \mathcal{L}^j if $\hat{\tau}^j > \lambda$. Using the implicit function theorem, we get

$$\frac{\partial(\sum_{j=1}^N k^j(\lambda))}{\partial \mathcal{L}^j} d\mathcal{L}^j + \frac{\partial(\sum_{j=1}^N k^j(\lambda))}{\partial \lambda} d\lambda = 0, \quad (\text{C.12})$$

which implies that

$$\frac{d\lambda}{d\mathcal{L}^j} = \frac{\log \left(\frac{\frac{\hat{\tau}^j}{\lambda} + \hat{\tau}^j \mathcal{L}^j}{1 + \hat{\tau}^j \mathcal{L}^j} \right) + \frac{\hat{\tau}^j \mathcal{L}^j (1 - \frac{\hat{\tau}^j}{\lambda})}{(\frac{\hat{\tau}^j}{\lambda} + \hat{\tau}^j \mathcal{L}^j)(1 + \hat{\tau}^j \mathcal{L}^j)}}{\sum_{j \in \mathbb{J}} \mathcal{L}^j \left(\frac{\frac{\hat{\tau}^j}{\lambda^2}}{\frac{\hat{\tau}^j}{\lambda} + \mathcal{L}^j} \right)}. \quad (\text{C.13})$$

Eq. (C.13) implies that $\frac{d\lambda}{d\mathcal{L}^j} > 0 \Leftrightarrow F(\frac{\hat{\tau}^j}{\lambda}, \hat{\tau}^j \mathcal{L}^j) > 0$, where we define

$$F(x, y) = \log\left(\frac{x+y}{1+y}\right) + \frac{y^j(1-x)}{(x+y)(1+y)}.$$

Notice that $F(1, y) = 0$ and $\partial F(x, y)/\partial x = x/(x+y)^2 > 0$ for all $x > 0$, which imply $\frac{d\lambda}{d\mathcal{L}^j} > 0$ for all i that satisfy $\lambda < \hat{\tau}^j$ and, therefore, $\hat{\tau}^j/\lambda > 1$. This finishes the proof. ■

Proof of Corollary 4.1. (i) For any asset r with $k^r > 0$, it is immediate from Eq. (41) that

$$\frac{dk^r}{d\lambda} = -\frac{\frac{\mathcal{L}^r}{\lambda^2}}{\frac{1}{\lambda} + \mathcal{L}^r} < 0. \quad (\text{C.14})$$

By the chain rule, we have

$$\frac{dk^r}{d\mathcal{L}^j} = \frac{dk^r}{d\lambda} \frac{d\lambda}{d\mathcal{L}^j} < 0. \quad \blacksquare \quad (\text{C.15})$$

(ii) This is immediate from the fact that (a) allocation k^r for any asset r with a positive allocation decrease in \mathcal{L}^j , and (b) the total resource K is fixed. Therefore, the resource allocation in asset j should increase in \mathcal{L}^j . ■

Proof of Lemma 4.1. We conjecture that the price function of each asset j is given by

$$p^j = f_1^j(\theta^j + \mu^j) - f_2^j z^j, \quad (\text{C.16})$$

where f_1^j and f_2^j are constants. Then, each investor infer the true value of θ^j using the sufficient statistic

$$\xi^j = \theta^j + \mu^j - \hat{f}_j^{-1} z^j,$$

where $\hat{f}_j = \frac{f_1^j}{f_2^j}$. Using the Bayes' theorem, the conditional expectation of each investor i is given by

$$E[\theta^j | S_i^j, \xi^j] = \alpha_i^j S_i^j + \beta_i^j \xi^j,$$

where

$$\alpha_i^j = \frac{\tau_\eta^j \tau_\mu^j}{(\tau_\theta^j + \tau_\mu^j)(\tau_\eta^j + \hat{f}_j^2 \tau_z^j) + \tau_\theta^j \tau_\mu^j}, \quad (\text{C.17})$$

$$\beta_i^j = \frac{\hat{f}_j^2 \tau_z^j \tau_\mu^j}{(\tau_\theta^j + \tau_\mu^j)(\tau_\eta^j + \hat{f}_j^2 \tau_z^j) + \tau_\theta^j \tau_\mu^j}. \quad (\text{C.18})$$

The conditional variance is also given by

$$\text{Var}[\theta^j | S_i^j, \xi^j] = \frac{\tau_\eta^j + \hat{f}_j^2 \tau_z^j + \tau_\mu^j}{(\tau_\theta^j + \tau_\mu^j)(\tau_\eta^j + \hat{f}_j^2 \tau_z^j) + \tau_\theta^j \tau_\mu^j}. \quad (\text{C.19})$$

Investor i 's demand for each asset j is given by the standard CARA-Gaussian demand:

$$x_i^j = \frac{E[\theta^j | S_i^j, \xi^j] - p^j}{\gamma \text{Var}[\theta | S_i^j, \xi^j]}, \quad (\text{C.20})$$

In equilibrium, the aggregate demand for each asset j should be equal to the supply:

$$\int x_i^j dj = z^j.$$

By solving for the price using the above market clearing condition, we confirm that our conjecture in Eq. (C.16) is indeed true.

$$f_1^j = \frac{\tau_\mu^j (\tau_\eta^j + \hat{f}_j^2 \tau_z^j)}{(\tau_\theta^j + \tau_\mu^j)(\tau_\eta^j + \hat{f}_j^2 \tau_z^j) + \tau_\theta^j \tau_\mu^j}, \quad (\text{C.21})$$

$$f_2^j = \frac{\hat{f}_j \tau_z^j \tau_\mu^j + \gamma (\tau_\eta^j + \hat{f}_j^2 \tau_z^j + \tau_\mu^j)}{(\tau_\theta^j + \tau_\mu^j)(\tau_\eta^j + \hat{f}_j^2 \tau_z^j) + \tau_\theta^j \tau_\mu^j}. \quad (\text{C.22})$$

Because $\hat{f}_j = \frac{f_1^j}{f_2^j}$, we get the following third-order equation using Eqs. (C.21) and (C.22) as follows:

$$\hat{f}_j = \frac{\tau_\mu^j (\tau_\eta^j + \hat{f}_j^2 \tau_z^j)}{\hat{f}_j \tau_z^j \tau_\mu^j + \gamma (\tau_\eta^j + \hat{f}_j^2 \tau_z^j + \tau_\mu^j)}.$$

Because there exists only one real root for the above equation, we get a unique solution for the pair (f_1^j, f_2^j) . Therefore, we have a unique linear equilibrium. ■

Proof of Proposition 4.2.

To prove the existence of an equilibrium, we first characterize the ex-ante optimization problem of each investor i . Notice that the investor's resource allocation problem is similar to the proof of Proposition 4.1 except that prices also reveal private information of other investors. Let $P = (p^1, p^2, \dots, p^N)$ denote be the vector of asset prices. Then, the value function for investor i 's optimal portfolio choice problem conditional on the acquired signals and the prices is given by

$$V_i(w_0; S_i, P) = \max_{x_i^1, x_i^2, \dots, x_i^N} E \left[-\exp \left(-\gamma \left(w_0 + \sum_{j=1}^N (\theta^j - p^j) x_i^j \right) \right) \middle| S_i, P \right] \quad (\text{C.23})$$

where x_i^j is the unit of holdings of asset j .

By Lemma C.2, we get

$$E[V_i(w_0; S_i, P)|P] = E \left[-\exp \left(-\gamma w_0 - \frac{1}{2} \sum_{j=1}^N \frac{(E[\theta^j | S_i^j, p^j] - p^j)^2}{\text{Var}[\theta^j | S_i^j, p^j]} \right) \middle| P \right] \quad (\text{C.24})$$

$$= -\prod_{j=1}^N \sqrt{\frac{\text{Var}[\theta^j | S_i^j, \xi^j]}{\text{Var}[\theta^j | \xi^j]}} \exp \left(-\gamma w_0 - \frac{1}{2} \sum_{j=1}^N \frac{(E[\theta^j | p^j] - p^j)^2}{\text{Var}[\theta^j | p^j]} \right). \quad (\text{C.25})$$

Therefore, the ex-ante expected utility can be obtained by taking an unconditional expectation on Eq. (C.25) as follows:²³

$$E[V_i(w_0; S_i, P)] = -\prod_{j=1}^N \left(\text{Var}[\theta^j | S_i^j, \xi^j] \right)^{\frac{1}{2}} \Gamma, \quad (\text{C.27})$$

where Γ is a constant unaffected by the choice of resource allocations such that

$$\Gamma = \prod_{j=1}^N \left(\text{Var}[\theta^j | \xi^j] \right)^{-\frac{1}{2}} E \left[\exp \left(-\gamma w_0 - \frac{1}{2} \sum_{j=1}^N \frac{(E[\theta^j | \xi^j] - p^j)^2}{\text{Var}[\theta^j | \xi^j]} \right) \right], \quad (\text{C.28})$$

Then, maximizing Eq. (C.27) under the resource constraint in Eq. (38) is equivalent to the following optimal resource allocation problem:

$$\max_{\sum_{j=1}^N k_i^j = K} \sum_{j=1}^N G_j(k_i^j) \quad (\text{C.29})$$

where $G_j(k_i^j) = -\log \left(\text{Var}[\theta^j | S_i^j, \xi^j] \right) = \log \left(\tau_\theta^j + g_j(k_i^j) \right)$ and

$$g_j(k_i^j) = \tau^j \mathcal{L}^j \left(1 - \frac{1}{\exp\left(\frac{k_i^j}{\mathcal{L}^j}\right) + (\tau^j \mathcal{L}^j)^{-1} \hat{f}_j^2 \tau_z^j} \right). \quad (\text{C.30})$$

²³Notice that $\text{Var}[\theta^j | \xi^j]$ and $\text{Var}[\theta^j | S_i^j, \xi^j]$ are both constants. For $\text{Var}[\theta^j | S_i^j, \xi^j]$, it is obvious from Eq. (??). $\text{Var}[\theta^j | \xi^j]$ is also a constant because

$$\text{Var}[\theta^j | \xi^j] = \frac{\tau_\mu}{\tau_\mu \tau_\theta + (\tau_\mu + \tau_\theta) \hat{f}_j^2 \tau_z}. \quad (\text{C.26})$$

Notice that $G_j(\cdot)$ is increasing in k_i^j because $G_j'(k_i^j) = \frac{g_j'(k_i^j)}{\tau_\theta + g_j(k_i^j)}$ and

$$g_j'(k_i^j) = \frac{\tau^j \exp(\frac{k_i^j}{\mathcal{L}^j})}{\left(\exp(\frac{k_i^j}{\mathcal{L}^j}) + (\tau^j \mathcal{L}^j)^{-1} \hat{f}_j^2 \tau_z^j\right)^2} > 0. \quad (\text{C.31})$$

Furthermore, we have

$$g_j''(k_i^j) = \frac{\frac{\tau^j}{\mathcal{L}^j} \exp(\frac{k_i^j}{\mathcal{L}^j})}{\left(\exp(\frac{k_i^j}{\mathcal{L}^j}) + (\tau^j \mathcal{L}^j)^{-1} \hat{f}_j^2 \tau_z^j\right)^2} \left[1 - \frac{2 \exp(\frac{k_i^j}{\mathcal{L}^j})}{\exp(\frac{k_i^j}{\mathcal{L}^j}) + (\tau^j \mathcal{L}^j)^{-1} \hat{f}_j^2 \tau_z^j} \right]. \quad (\text{C.32})$$

Then, $G_j(\cdot)$ is concave if and only if $g_j''(k_i^j)(\tau_\theta + g_j(k_i^j)) < g_j'(k_i^j)^2$ for all k_i^j . Since \hat{f}_j has a finite limit as $\tau_z^j \rightarrow 0$,²⁴ then Eq. (C.32) implies $\lim_{\tau_z^j \rightarrow 0} g_j''(k_i^j) < 0$. Because $G_j(\cdot)$ is continuous in τ_z^j , there exists a constant $\bar{\tau}_z^j$ such that $G_j(\cdot)$ is strictly concave for all $\tau_z^j < \bar{\tau}_z^j$. Under this parametric assumption, we can solve the optimization problem in Eq. (C.29) by solving the following for each asset j :

$$G_j^*(\lambda) = \min_{k_i^j \geq 0} \left(\lambda k_i^j - \log \left(\tau_\theta^j + g_j(k_i^j) \right) \right). \quad (\text{C.33})$$

Then, a corner solution $k_i^j = 0$ is optimal whenever the marginal increase in the objective function of Eq. (C.33) at $k_i^j = 0$ is non-negative:

$$\lambda - \bar{\lambda}^j \geq 0, \quad (\text{C.34})$$

where

$$\bar{\lambda}^j \equiv \frac{g_j'(k_i^j)}{\tau_\theta^j + g_j(k_i^j)} \Big|_{k_i^j=0} = \frac{\hat{\tau}^j}{\left(1 + (\tau^j \mathcal{L}^j)^{-1} \hat{f}_j^2 \tau_z^j\right) \left(1 + (\tau_\theta^{-1} + (\tau^j \mathcal{L}^j)^{-1}) \hat{f}_j^2 \tau_z^j\right)}. \quad (\text{C.35})$$

Otherwise, the optimal choice of k_i^j can be obtained by solving the following equation, which is the first-order condition from Eq. (C.33), as follows:

$$\exp\left(\frac{2k_i^j}{\mathcal{L}^j}\right) - 2A^j \exp\left(\frac{k_i^j}{\mathcal{L}^j}\right) + B^j = 0, \quad (\text{C.36})$$

where

$$A^j = \frac{1}{2} \left(\frac{\hat{\tau}^j}{\lambda} + \hat{\tau}^j \mathcal{L}^j \right) - (\tau^j \mathcal{L}^j)^{-1} \hat{f}_j^2 \tau_z^j; \quad (\text{C.37})$$

²⁴See, for example, Hellwig (1980) for the proof.

$$B^j = (\tau^j \mathcal{L}^j)^{-1} \hat{f}_j^2 \tau_z^j \left[(\tau^j \mathcal{L}^j)^{-1} \hat{f}_j^2 \tau_z^j - \frac{\hat{\tau}^j \mathcal{L}^j}{1 + \hat{\tau}^j \mathcal{L}^j} \right]. \quad (\text{C.38})$$

Note that letting $\tau_p^j = \hat{f}_j^2 \tau_z^j$ gives the expressions for $\bar{\lambda}^j, A^j$ and B^j in the main text.

The quadratic exponential equation in Eq. (C.36) has two solutions, but only one of them is real whenever $\lambda < \bar{\lambda}^j$, so we have the following unique optimal allocation k_i^j for each asset j given λ as follows:

$$k_i^j(\lambda) = \begin{cases} \mathcal{L}^j \log \left(A^j + \sqrt{(A^j)^2 - B^j} \right) & \text{if } 0 < \lambda < \bar{\lambda}^j \\ 0 & \text{if } \lambda \geq \bar{\lambda}^j \end{cases} \quad (\text{C.39})$$

where λ solves

$$\sum_{j=1}^N k_i^j(\lambda) = K.$$

Furthermore, the solution is unique because each $k_i^j(\lambda)$ is decreasing in λ as in the proof of Proposition 4.1.

Now, we turn to the proof of existence of equilibrium. Suppose that the equilibrium resource allocation is given by a vector $\bar{\kappa} = (\kappa^1, \kappa^2, \dots, \kappa^N)$. Lemma 4.1 shows that there always exists a unique pair of f_1^j and f_2^j for each asset j given the vector $\bar{\kappa}$. Thus, there exists a unique $\hat{f}_j = \frac{f_1^j}{f_2^j}$ for each asset j given the vector $\bar{\kappa}$. Furthermore, it is obvious from Eq. (43) that \hat{f}_j is continuous in $\bar{\kappa}$ because it is continuous in τ_η^j and τ_μ^j which are also continuous in $\bar{\kappa}$ due to Corollary 2.1.

Let $\mathbb{K} = \{k^1, k^2, \dots, k^N | k^1 + k^2 + \dots + k^N = K\}$ be a simplex that includes all the feasible choices of resource allocations. By Eq. (C.39), it is immediate that there exists a unique mapping that $\Psi : \mathbb{K} \rightarrow \mathbb{K}$ that maps the given equilibrium resource allocation to each investor's individually-optimal choice. The overall equilibrium exists when the given equilibrium allocation is indeed individually-optimal, i.e., $\bar{\kappa} = \Psi(\bar{\kappa})$. Therefore, the equilibrium existence proof reduces to the proof of showing the existence of a fixed point for the mapping $\Psi(\cdot)$. Because the optimal choice mapping $\Psi(\cdot)$ is a continuous mapping from the non-empty, convex and compact set \mathbb{K} to \mathbb{K} , there exists a fixed point for the mapping due to Kakutani fixed point theorem. This finishes the proof. ■

References

- Admati, A. R., 1985, "A Noisy Rational Expectations Equilibrium for Multi-Asset Securities Markets," *American Economic Review*, 53(3), 629–657.
- Billingsley, P., 1979, *Probability and measure*. John Wiley & Sons, Hoboken, NJ.
- Black, F., 1974, "International capital market equilibrium with investment barriers," *Journal of Financial Economics*, 1(4), 337–352.

- Colombo, L., G. Femminis, and A. Pavan, 2014, "Information Acquisition and Welfare," *Review of Economic Studies*, 81(4), 1438–1483.
- Dow, J., and R. Rahi, 2003, "Informed Trading, Investment and Welfare," *Journal of Business*, 76(3), 439–454.
- Grossman, S. J., and J. E. Stiglitz, 1980, "On the Impossibility of Informationally Efficient Markets," *American Economic Review*, 70(3), 393–408.
- Hellwig, C., and L. Veldkamp, 2009, "Knowing What Others Know: Coordination Motives in Information Acquisition," *Review of Economic Studies*, 76, 223–251.
- Hellwig, M. F., 1980, "On the Aggregation of Information in Competitive Markets," *Journal of Economic Theory*, 22, 477–498.
- Hou, K., and T. J. Moskowitz, 2005, "Market Frictions, Price Delay, and the Cross-Section of Expected Returns," *Review of Financial Studies*, 18(3), 981–1020.
- Kahneman, D., 1973, *Attention and Effort*. Prentice-Hall, Englewood Cliffs, NJ.
- Kreps, D. M., and E. L. Porteus, 1978, "Temporal Resolution of Uncertainty and Dynamic Choice Theory," *ema*, 46(1), 185–200.
- Kyle, A. S., 1985, "Continuous Auctions and Insider Trading," *Econometrica*, 53(6), 1315–1335.
- Manzano, C., and X. Vives, 2011, "Public and private learning from prices, strategic substitutability and complementarity, and equilibrium multiplicity," *Journal of Mathematical Economics*, 47(3), 346–369.
- Marschak, J., 1974, "Limited Role of Entropy in Information Economics," *Theory and Decision*, 5(1), 1–7.
- Mondria, J., 2010, "Portfolio choice, attention allocation, and price comovement," *Journal of Economic Theory*, 145(5), 1837–1864.
- Morris, S., and H. S. Shin, 2002, "Social Value of Public Information," *American Economic Review*, 92(5), 1521–1534.
- Moscarini, G., and L. Smith, 2001, "The Optimal Level of Experimentation," *Econometrica*, 69(6), 1629–1644.
- Myatt, D. P., and C. Wallace, 2012, "Information Acquisition and Welfare," *Review of Economic Studies*, 79(1), 340–374.
- Peng, L., 2005, "Learning with Information Capacity Constraints," *Journal of Financial and Quantitative Analysis*, 40, 307–329.

- Peress, J., 2004, "Wealth, Information Acquisition and Portfolio Choice," *Review of Financial Studies*, 17(2), 879–914.
- Portes, R., and H. Rey, 2005, "The determinants of cross-border equity flows," *Journal of international Economics*, 65(2), 269–296.
- Ritter, F. E., and L. J. Schooler, 2001, "The Learning Curve," in *International Encyclopedia of the Social and Behavioral Sciences*. Pergamon, Amsterdam, pp. 8602–8605.
- Shannon, C. E., 1948, "A Mathematical Theory of Communication," *The Bell System Technical Journal*, 27, 379–423, 623–656.
- Sims, C. A., 2003, "Implication of Rational Inattention," *Journal of Monetary Economics*, 50, 665–690.
- Stadje, W., 1990, "The Collector's Problem with Group Drawings," *Advances in Applied Probability*, 22(4), 866–882.
- Van der Vaart, A. W., 2000, *Asymptotic statistics*. Cambridge university press, Cambridge.
- Van Nieuwerburgh, S., and L. Veldkamp, 2009, "Information Immobility and the Home Bias Puzzle," *Journal of Finance*, 3, 118–1215.
- , 2010, "Information Acquisition and Under-Diversification," *Review of Economic Studies*, 2, 779–805.
- Veldkamp, L. L., 2011, *Information choice in macroeconomics and finance*. Princeton University Press, Princeton, New Jersey.

Earlier Working Papers:

For a complete list of Working Papers published by Sveriges Riksbank, see www.riksbank.se

Estimation of an Adaptive Stock Market Model with Heterogeneous Agents <i>by Henrik Amilon</i>	2005:177
Some Further Evidence on Interest-Rate Smoothing: The Role of Measurement Errors in the Output Gap <i>by Mikael Apel and Per Jansson</i>	2005:178
Bayesian Estimation of an Open Economy DSGE Model with Incomplete Pass-Through <i>by Malin Adolphson, Stefan Laséen, Jesper Lindé and Mattias Villani</i>	2005:179
Are Constant Interest Rate Forecasts Modest Interventions? Evidence from an Estimated Open Economy DSGE Model of the Euro Area <i>by Malin Adolphson, Stefan Laséen, Jesper Lindé and Mattias Villani</i>	2005:180
Inference in Vector Autoregressive Models with an Informative Prior on the Steady State <i>by Mattias Villani</i>	2005:181
Bank Mergers, Competition and Liquidity <i>by Elena Carletti, Philipp Hartmann and Giancarlo Spagnolo</i>	2005:182
Testing Near-Rationality using Detailed Survey Data <i>by Michael F. Bryan and Stefan Palmqvist</i>	2005:183
Exploring Interactions between Real Activity and the Financial Stance <i>by Tor Jacobson, Jesper Lindé and Kasper Roszbach</i>	2005:184
Two-Sided Network Effects, Bank Interchange Fees, and the Allocation of Fixed Costs <i>by Mats A. Bergman</i>	2005:185
Trade Deficits in the Baltic States: How Long Will the Party Last? <i>by Rudolfs Bems and Kristian Jönsson</i>	2005:186
Real Exchange Rate and Consumption Fluctuations following Trade Liberalization <i>by Kristian Jönsson</i>	2005:187
Modern Forecasting Models in Action: Improving Macroeconomic Analyses at Central Banks <i>by Malin Adolphson, Michael K. Andersson, Jesper Lindé, Mattias Villani and Anders Vredin</i>	2005:188
Bayesian Inference of General Linear Restrictions on the Cointegration Space <i>by Mattias Villani</i>	2005:189
Forecasting Performance of an Open Economy Dynamic Stochastic General Equilibrium Model <i>by Malin Adolphson, Stefan Laséen, Jesper Lindé and Mattias Villani</i>	2005:190
Forecast Combination and Model Averaging using Predictive Measures <i>by Jana Eklund and Sune Karlsson</i>	2005:191
Swedish Intervention and the Krona Float, 1993-2002 <i>by Owen F. Humpage and Javiera Ragnartz</i>	2006:192
A Simultaneous Model of the Swedish Krona, the US Dollar and the Euro <i>by Hans Lindblad and Peter Sellin</i>	2006:193
Testing Theories of Job Creation: Does Supply Create Its Own Demand? <i>by Mikael Carlsson, Stefan Eriksson and Nils Gottfries</i>	2006:194
Down or Out: Assessing The Welfare Costs of Household Investment Mistakes <i>by Laurent E. Calvet, John Y. Campbell and Paolo Sodini</i>	2006:195
Efficient Bayesian Inference for Multiple Change-Point and Mixture Innovation Models <i>by Paolo Giordani and Robert Kohn</i>	2006:196
Derivation and Estimation of a New Keynesian Phillips Curve in a Small Open Economy <i>by Karolina Holmberg</i>	2006:197
Technology Shocks and the Labour-Input Response: Evidence from Firm-Level Data <i>by Mikael Carlsson and Jon Smedsaas</i>	2006:198
Monetary Policy and Staggered Wage Bargaining when Prices are Sticky <i>by Mikael Carlsson and Andreas Westermark</i>	2006:199
The Swedish External Position and the Krona <i>by Philip R. Lane</i>	2006:200

Price Setting Transactions and the Role of Denominating Currency in FX Markets <i>by Richard Friberg and Fredrik Wilander</i>	2007:201
The geography of asset holdings: Evidence from Sweden <i>by Nicolas Coeurdacier and Philippe Martin</i>	2007:202
Evaluating An Estimated New Keynesian Small Open Economy Model <i>by Malin Adolfson, Stefan Laséen, Jesper Lindé and Mattias Villani</i>	2007:203
The Use of Cash and the Size of the Shadow Economy in Sweden <i>by Gabriela Guibourg and Björn Segendorf</i>	2007:204
Bank supervision Russian style: Evidence of conflicts between micro- and macro-prudential concerns <i>by Sophie Claeys and Koen Schoors</i>	2007:205
Optimal Monetary Policy under Downward Nominal Wage Rigidity <i>by Mikael Carlsson and Andreas Westermarck</i>	2007:206
Financial Structure, Managerial Compensation and Monitoring <i>by Vittoria Cerasi and Sonja Daltung</i>	2007:207
Financial Frictions, Investment and Tobin's q <i>by Guido Lorenzoni and Karl Walentin</i>	2007:208
Sticky Information vs Sticky Prices: A Horse Race in a DSGE Framework <i>by Mathias Trabandt</i>	2007:209
Acquisition versus greenfield: The impact of the mode of foreign bank entry on information and bank lending rates <i>by Sophie Claeys and Christa Hainz</i>	2007:210
Nonparametric Regression Density Estimation Using Smoothly Varying Normal Mixtures <i>by Mattias Villani, Robert Kohn and Paolo Giordani</i>	2007:211
The Costs of Paying – Private and Social Costs of Cash and Card <i>by Mats Bergman, Gabriella Guibourg and Björn Segendorf</i>	2007:212
Using a New Open Economy Macroeconomics model to make real nominal exchange rate forecasts <i>by Peter Sellin</i>	2007:213
Introducing Financial Frictions and Unemployment into a Small Open Economy Model <i>by Lawrence J. Christiano, Mathias Trabandt and Karl Walentin</i>	2007:214
Earnings Inequality and the Equity Premium <i>by Karl Walentin</i>	2007:215
Bayesian forecast combination for VAR models <i>by Michael K. Andersson and Sune Karlsson</i>	2007:216
Do Central Banks React to House Prices? <i>by Daria Finocchiaro and Virginia Queijo von Heideken</i>	2007:217
The Riksbank's Forecasting Performance <i>by Michael K. Andersson, Gustav Karlsson and Josef Svensson</i>	2007:218
Macroeconomic Impact on Expected Default Frequency <i>by Per Åsberg and Hovick Shahnazarian</i>	2008:219
Monetary Policy Regimes and the Volatility of Long-Term Interest Rates <i>by Virginia Queijo von Heideken</i>	2008:220
Governing the Governors: A Clinical Study of Central Banks <i>by Lars Frisell, Kasper Roszbach and Giancarlo Spagnolo</i>	2008:221
The Monetary Policy Decision-Making Process and the Term Structure of Interest Rates <i>by Hans Dillén</i>	2008:222
How Important are Financial Frictions in the U S and the Euro Area <i>by Virginia Queijo von Heideken</i>	2008:223
Block Kalman filtering for large-scale DSGE models <i>by Ingvar Strid and Karl Walentin</i>	2008:224
Optimal Monetary Policy in an Operational Medium-Sized DSGE Model <i>by Malin Adolfson, Stefan Laséen, Jesper Lindé and Lars E. O. Svensson</i>	2008:225
Firm Default and Aggregate Fluctuations <i>by Tor Jacobson, Rikard Kindell, Jesper Lindé and Kasper Roszbach</i>	2008:226

Re-Evaluating Swedish Membership in EMU: Evidence from an Estimated Model <i>by Ulf Söderström</i>	2008:227
The Effect of Cash Flow on Investment: An Empirical Test of the Balance Sheet Channel <i>by Ola Melander</i>	2009:228
Expectation Driven Business Cycles with Limited Enforcement <i>by Karl Walentin</i>	2009:229
Effects of Organizational Change on Firm Productivity <i>by Christina Håkanson</i>	2009:230
Evaluating Microfoundations for Aggregate Price Rigidities: Evidence from Matched Firm-Level Data on Product Prices and Unit Labor Cost <i>by Mikael Carlsson and Oskar Nordström Skans</i>	2009:231
Monetary Policy Trade-Offs in an Estimated Open-Economy DSGE Model <i>by Malin Adolfson, Stefan Laséen, Jesper Lindé and Lars E. O. Svensson</i>	2009:232
Flexible Modeling of Conditional Distributions Using Smooth Mixtures of Asymmetric Student T Densities <i>by Feng Li, Mattias Villani and Robert Kohn</i>	2009:233
Forecasting Macroeconomic Time Series with Locally Adaptive Signal Extraction <i>by Paolo Giordani and Mattias Villani</i>	2009:234
Evaluating Monetary Policy <i>by Lars E. O. Svensson</i>	2009:235
Risk Premiums and Macroeconomic Dynamics in a Heterogeneous Agent Model <i>by Ferre De Graeve, Maarten Dossche, Marina Emiris, Henri Sneessens and Raf Wouters</i>	2010:236
Picking the Brains of MPC Members <i>by Mikael Apel, Carl Andreas Claussen and Petra Lennartsdotter</i>	2010:237
Involuntary Unemployment and the Business Cycle <i>by Lawrence J. Christiano, Mathias Trabandt and Karl Walentin</i>	2010:238
Housing collateral and the monetary transmission mechanism <i>by Karl Walentin and Peter Sellin</i>	2010:239
The Discursive Dilemma in Monetary Policy <i>by Carl Andreas Claussen and Øistein Røisland</i>	2010:240
Monetary Regime Change and Business Cycles <i>by Vasco Cúrdia and Daria Finocchiaro</i>	2010:241
Bayesian Inference in Structural Second-Price common Value Auctions <i>by Bertil Wegmann and Mattias Villani</i>	2010:242
Equilibrium asset prices and the wealth distribution with inattentive consumers <i>by Daria Finocchiaro</i>	2010:243
Identifying VARs through Heterogeneity: An Application to Bank Runs <i>by Ferre De Graeve and Alexei Karas</i>	2010:244
Modeling Conditional Densities Using Finite Smooth Mixtures <i>by Feng Li, Mattias Villani and Robert Kohn</i>	2010:245
The Output Gap, the Labor Wedge, and the Dynamic Behavior of Hours <i>by Luca Sala, Ulf Söderström and Antonella Trigari</i>	2010:246
Density-Conditional Forecasts in Dynamic Multivariate Models <i>by Michael K. Andersson, Stefan Palmqvist and Daniel F. Waggoner</i>	2010:247
Anticipated Alternative Policy-Rate Paths in Policy Simulations <i>by Stefan Laséen and Lars E. O. Svensson</i>	2010:248
MOSES: Model of Swedish Economic Studies <i>by Gunnar Bårdsen, Ard den Reijer, Patrik Jonasson and Ragnar Nymoén</i>	2011:249
The Effects of Endogenous Firm Exit on Business Cycle Dynamics and Optimal Fiscal Policy <i>by Lauri Vilmi</i>	2011:250
Parameter Identification in a Estimated New Keynesian Open Economy Model <i>by Malin Adolfson and Jesper Lindé</i>	2011:251
Up for count? Central bank words and financial stress <i>by Marianna Blix Grimaldi</i>	2011:252

Wage Adjustment and Productivity Shocks <i>by Mikael Carlsson, Julián Messina and Oskar Nordström Skans</i>	2011:253
Stylized (Arte) Facts on Sectoral Inflation <i>by Ferre De Graeve and Karl Walentin</i>	2011:254
Hedging Labor Income Risk <i>by Sebastien Betermier, Thomas Jansson, Christine A. ParLOUR and Johan Walden</i>	2011:255
Taking the Twists into Account: Predicting Firm Bankruptcy Risk with Splines of Financial Ratios <i>by Paolo Giordani, Tor Jacobson, Erik von Schedvin and Mattias Villani</i>	2011:256
Collateralization, Bank Loan Rates and Monitoring: Evidence from a Natural Experiment <i>by Geraldo Cerqueiro, Steven Ongena and Kasper Roszbach</i>	2012:257
On the Non-Exclusivity of Loan Contracts: An Empirical Investigation <i>by Hans Degryse, Vasso Ioannidou and Erik von Schedvin</i>	2012:258
Labor-Market Frictions and Optimal Inflation <i>by Mikael Carlsson and Andreas Westermark</i>	2012:259
Output Gaps and Robust Monetary Policy Rules <i>by Roberto M. Billi</i>	2012:260
The Information Content of Central Bank Minutes <i>by Mikael Apel and Marianna Blix Grimaldi</i>	2012:261
The Cost of Consumer Payments in Sweden <i>by Björn Segendorf and Thomas Jansson</i>	2012:262
Trade Credit and the Propagation of Corporate Failure: An Empirical Analysis <i>by Tor Jacobson and Erik von Schedvin</i>	2012:263
Structural and Cyclical Forces in the Labor Market During the Great Recession: Cross-Country Evidence <i>by Luca Sala, Ulf Söderström and Antonella Trigari</i>	2012:264
Pension Wealth and Household Savings in Europe: Evidence from SHARELIFE <i>by Rob Alessie, Viola Angelini and Peter van Santen</i>	2013:265
Long-Term Relationship Bargaining <i>by Andreas Westermark</i>	2013:266
Using Financial Markets To Estimate the Macro Effects of Monetary Policy: An Impact-Identified FAVAR* <i>by Stefan Pitschner</i>	2013:267
DYNAMIC MIXTURE-OF-EXPERTS MODELS FOR LONGITUDINAL AND DISCRETE-TIME SURVIVAL DATA <i>by Matias Quiroz and Mattias Villani</i>	2013:268
Conditional euro area sovereign default risk <i>by André Lucas, Bernd Schwaab and Xin Zhang</i>	2013:269
Nominal GDP Targeting and the Zero Lower Bound: Should We Abandon Inflation Targeting?*	2013:270
<i>by Roberto M. Billi</i>	
Un-truncating VARs* <i>by Ferre De Graeve and Andreas Westermark</i>	2013:271
Housing Choices and Labor Income Risk <i>by Thomas Jansson</i>	2013:272
Identifying Fiscal Inflation* <i>by Ferre De Graeve and Virginia Queijo von Heideken</i>	2013:273
On the Redistributive Effects of Inflation: an International Perspective* <i>by Paola Boel</i>	2013:274
Business Cycle Implications of Mortgage Spreads* <i>by Karl Walentin</i>	2013:275
Approximate dynamic programming with post-decision states as a solution method for dynamic economic models <i>by Isaiah Hull</i>	2013:276
A detrimental feedback loop: deleveraging and adverse selection <i>by Christoph Bertsch</i>	2013:277
Distortionary Fiscal Policy and Monetary Policy Goals <i>by Klaus Adam and Roberto M. Billi</i>	2013:278
Predicting the Spread of Financial Innovations: An Epidemiological Approach <i>by Isaiah Hull</i>	2013:279

Firm-Level Evidence of Shifts in the Supply of Credit <i>by Karolina Holmberg</i>	2013:280
Lines of Credit and Investment: Firm-Level Evidence of Real Effects of the Financial Crisis <i>by Karolina Holmberg</i>	2013:281
A wake-up call: information contagion and strategic uncertainty <i>by Toni Ahnert and Christoph Bertsch</i>	2013:282
Debt Dynamics and Monetary Policy: A Note <i>by Stefan Laséen and Ingvar Strid</i>	2013:283
Optimal taxation with home production <i>by Conny Olovsson</i>	2014:284
Incompatible European Partners? Cultural Predispositions and Household Financial Behavior <i>by Michael Haliassos, Thomas Jansson and Yigitcan Karabulut</i>	2014:285
How Subprime Borrowers and Mortgage Brokers Shared the Pecial Behavior <i>by Antje Berndt, Burton Hollifield and Patrik Sandås</i>	2014:286
The Macro-Financial Implications of House Price-Indexed Mortgage Contracts <i>by Isaiah Hull</i>	2014:287
Does Trading Anonymously Enhance Liquidity? <i>by Patrick J. Dennis and Patrik Sandås</i>	2014:288
Systematic bailout guarantees and tacit coordination <i>by Christoph Bertsch, Claudio Calcagno and Mark Le Quement</i>	2014:289
Selection Effects in Producer-Price Setting <i>by Mikael Carlsson</i>	2014:290
Dynamic Demand Adjustment and Exchange Rate Volatility <i>by Vesna Corbo</i>	2014:291
Forward Guidance and Long Term Interest Rates: Inspecting the Mechanism <i>by Ferre De Graeve, Pelin Ilbas & Raf Wouters</i>	2014:292
Firm-Level Shocks and Labor Adjustments <i>by Mikael Carlsson, Julián Messina and Oskar Nordström Skans</i>	2014:293
A wake-up call theory of contagion <i>by Toni Ahnert and Christoph Bertsch</i>	2015:294
Risks in macroeconomic fundamentals and excess bond returns predictability <i>by Rafael B. De Rezende</i>	2015:295
The Importance of Reallocation for Productivity Growth: Evidence from European and US Banking <i>by Jaap W.B. Bos and Peter C. van Santen</i>	2015:296
SPEEDING UP MCMC BY EFFICIENT DATA SUBSAMPLING <i>by Matias Quiroz, Mattias Villani and Robert Kohn</i>	2015:297
Amortization Requirements and Household Indebtedness: An Application to Swedish-Style Mortgages <i>by Isaiah Hull</i>	2015:298
Fuel for Economic Growth? <i>by Johan Gars and Conny Olovsson</i>	2015:299



Sveriges Riksbank
Visiting address: Brunkebergs torg 11
Mail address: se-103 37 Stockholm

Website: www.riksbank.se
Telephone: +46 8 787 00 00, Fax: +46 8 21 05 31
E-mail: registratorn@riksbank.se