Information acquisition in financial markets through artificial intelligence (Early stage work)*

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Abstract

Investors choose the level of costly deployment of artificial intelligence (AI) models, such as large language models, to better extract signal about fundamentals from a noisy and multidimensional common data space. The monotonically increasing technology evolves over time but both this evolution and the actual adoption depends on the use of scarce resources, mimicking constraints in human resources and parallel computing. Investors decide to invest on a risky asset with strategic complementarities on information and on the level of technology adoption by peers. The model features the possibility of hallucinations or other silent mistakes in information processing. The model is simple but allows inference on important topics related to the adoption of AI in finance, including the effect of hallucinations on the coordination of investors, the role of a closed versus open AI model, the potentially outsized effects of cyber security or other operational risk incidents, and supply chain shocks in the AI chip industry. JEL codes: D82, G14.

"*Firms making investment decisions are starting to emulate the hair-trigger behaviour of financial investors. That means that a growing part of the economy may be starting to act like a financial market, with all that implies—like the potential for bubbles and panics. One could argue that far from making the economy more stable, the rapid responses of today's corporations make their investment in equipment and software vulnerable to the kind of self-fulfilling pessimism that used to be possible only for investment in paper assets.*" - Krugman (2001)

1 Introduction

The increasing capabilities of large language models (LLM) and other artificial intelligence (AI) models unlock useful new ways to transform data into actionable information, expanding the "data envelope" (Bonney et al. (2024)). These sophisticated models have been posited to be useful even for forecasting and

*This work represents my opinion and not necessarily that of the BIS.

stock trading (eg, Lopez-Lira and Tang (2023)), adding further momentum to the use of these technologies. But while AI may better transform data into information, increasing precision about a private signal, it also can output silent errors, such as hallucinations, that are hard to identify. For example, LLMs might provide human-like answers that fail to correctly identify trivial aspects of tasks (Perez-Cruz and Shin (2024)). Another consideration is the cost of investing in edge AI applications for deployment at scale. And since AI-specific resources such as skilled labour force and adequate chips are very limited, even AI developers might be affected.

All these issues add to the usual incomplete information setting that is traditionally studied in financial markets (Morris and Shin (2002), Morris and Shin (2003), Szkup and Trevino (2020)). If each investor expects others to improve their own signal-to-noise ratio by adopting a common technology, a coordination situation similar to the canonical global games arises, playing out together with the original coordination issue. This paper explores such games when a technology evolves according to availability of resources that are also deployed at a cost by market participants to improve their signal.

Market participants choose the level of costly deployment of artificial intelligence models, such as large language models, to better extract signal about fundamentals from a noisy and multidimensional common data space. The monotonically increasing technology frontier evolves over time but actual adoption depends on the use of scarce resources that influence costs, mimicking constraints in human resources and parallel computing. Participants make decisions based on a 'double global game' with simultaneous higher-order beliefs about asset prices and technology adoption by peers. Similar to the traditional case with assets, participants overinvest in AI because they think others might be doing so, etc. But while this overinvestment in AI reduces the noise about fundamentals, the higher-order beliefs that everyone else also observes lower noise ends up leading to the same theme of overinvestment in the asset as well. If the technology envelope does not include a properly reasoning AI model, which is able to robustly ignore noise about fundamentals, the equilibrium outcome is a self-reinforcing overinvestment both in the asset and in the AI-related resources. In contrast, the emergence of a reasoning model brings the noise to zero and agents coordinate perfectly.

The model is simple enough to represent the main dynamics of investors' indirect acquisition of information through their investment in AI. At the same time, it contains rich enough representations that allow the study of questions of interest. In this paper I explore four of them. First, the model allows for an AI to fully reason with respect to an input and task. Second, given discussions around the wisedom of open source versus closed source models, the mode shines a light on the role of a closed versus open AI model. Third, analyses demonstrate the potentially outsized effects of cyber security or other operational risk incidents, and finally the supply chain shocks in the AI chip industry are simulated.

1.1 Literature

This work relates to the literatures on information acquisition in incomplete information games, and on AI and data in finance. **Coordination with information acquisition**. Angeletos and Lian (2016), Szkup and Trevino (2015b), Szkup and Trevino (2015a), Szkup and Trevino (2021). Reshidi et al. (2021) study the individual and collective information acquisition. Technology adoption canonical model D. Frankel and Pauzner (2000). Private aquisition of information (processing), Hellwig and Veldkamp (2009) and Colombo, Femminis, and Pavan (2014). Colombo, Femminis, and Pavan (2014) highlights the difference between effiencies in information acquisition and its usage. In contrast with that literature, here the AI technology frontier also develops endogenously and responds (negatively) to the resource take-up from technology adoption… **Global games**. Carlsson and Van Damme (1993). Morris and Shin (2002), Morris and Shin (2003).

Data in finance Farboodi et al. (2022) models the extraction by investors of *information* on assets from *data*, and how the value of data is related also to characteristics of the asset itself. Begenau, Farboodi, and Veldkamp (2018) argues that the existence of more data to larger firms favours them over others. **AI in finance, including risks.** AI can read information better (Araujo et al. (n.d.), Araujo et al. (2024)), and especially the more sophisticated type of models - large language models (LLMs) can further increase the ability to use data (Korinek (2023)). Lopez-Lira and Tang (2023) show evidence that ChatGPT, the flagship LLM, can successfully pick stocks. Danielsson, Macrae, and Uthemann (2022) discuss risks.

2 Model

The model draws from the setup in Szkup and Trevino (2021), with important additions. First, the cost of technology adoption is subject to a flat supply curve, resulting in cost changes that introduce another strategic complementarity. Second, the technology itself evolves stochastically over time, including in response to factor prices as well. And third, the process by which AI improves the signal is laid out in more detail to highlight the cases where the technology can transform more data text into inormation but cannot yet *reason* about it.

2.1 Setup

The simplest version of the model is a two-investor setup as follows.

The state of economic fundamentals is a random variable with normal distribution $\theta \sim N(\mu_\theta, \sigma_\theta^2)$. θ is only observed indirectly by each investor i as a noisy signal, $x_i = \theta + \sigma_i \epsilon_i$. An AI technology $\alpha(R) > 0$ uses finite specialised resources R (eg, AI scientists, data engineers, graphics processing units chips - GPUs, etc) to improve the precision of the signal of the existing data. The total amount of these resources is divided into AI developers and the investors:

$R = R_{\text{AI}} + \sum_i R_i$ for $R_{\text{AI}} > 0$ and $\forall R_i \geq 0$. The technology has decreasing returns to scale with $\alpha'_R > 0, \alpha''_R < 0$, and each individual precision defined as $\sigma_i = \sigma/\alpha(R_i)$. α itself is common amongst players, reflecting the current relevance of open source and open weight models in the high end AI market. However, section Section 6 relaxes this definition so that investors can also purchase a unique α_i technology.

However, unless the AI model can actually reason, very precise signals (low σ_i) also increase the risk of belieavable wrong answers (such as "hallucinations") or other forms of "silent mistakes", which bias the investor's perception about fundamentals. Such a problem is of course compounded by the high confidence the investor has in the signal given its acquired low σ_i. This is modelled through a *reasoning filter* ϕ (see Section 4). This function is the identity function if the AI cannot reason and 0 if it can reason. Having $\eta \sim N(0, \sigma_\eta)$ as the baseline level of noise[1] for all private signals, then each investor will observe $\epsilon_i = \eta + \phi(e^{\lambda \alpha_i(R)})$, in which λ is an inconsequential positive constant for scaling only. Putting all of this together, the private signal about the fundamentals is:

$$x_i = \theta + (\eta + \phi(e^{\lambda \alpha(R_i)}))\sigma/\alpha(R_i) \tag{1}$$

Given this scenario for technology investment, two ex ante identical investors $i \in \{1, 2\}$ choose how much R_i to acquire. Because resources are finite and technologists pick up the residual resources not acquired by investors, the investors face a supply curve and the technologists are assumed for simplicity to be price takers. Given this structure, prices are normalised as the proportion of resources taken by investors, $\rho = (1/R)\sum_i R_i$.[2]. The prices are public information and the market for AI resources clear.

The two investors decide in the first stage how much of their endowment to invest in AI usage, with the remainder available for the next stage where they decide whether or not to invest, $a_i \in \{0, 1\}$. This equality is represented as $E_i = R_i + I_i$. In the second period, the investors decide how to allocate I_i, in a safe or risky asset (the allocation is binary). The safe asset does not have a cost, and yields zero regardless of θ or the number of investors who choose it. Conversely, the risk asset's payoff can be successful in either of the following situations: (a) if $\theta \geq \bar{\theta}$ or (b) if $\theta \geq \underline{\theta}$ and $A_i = A_j = 1$. While this payoff structure follows Szkup and Trevino (2021) closely, the current model differs from that one because investors only allocates I_i. Because investing in the risky asset entails a cost T, the risky asset yields $\theta I_i - T$ in case of success or alternatively, $-T$.

Each investor's choice a_i depends on the observed signal x_i and the level of use of AI chosen in the preceding step, R_i. As in Szkup and Trevino (2021), the level

[1] Reflecting, for example, technology frictions in the production and dissemination of data, or more fundamentally even the sparsity in the actual signal from the manifold hypothesis.

[2] The actual prices could be proportional to this ratio, but the added clutter to notation does not justify it.

of precision (from the investment in AI resources) is common knowledge in this simple game, but here it is only incidentally so: this settings comports only two investors and a common price that reflects their joint AI investments.[3] Each investor's utility is a mapping of the form $u : \{0,1\} \times \{0,1\} \times \mathbf{R} \times [0,1] \to \mathbf{R}$, with $u(A_i, A_j, x_i, R_i)$ representing investor i's pay-off as a function of their own action, the other investor's action, the signal observed by i, and its investment in the AI technology.

In concrete terms,

$$u(A_i, A_j, x_i, R_i) = (\mathbf{1}[\theta \geq \bar{\theta}|x_i] + \mathbf{1}[x_i \geq x_i^*|\theta]a_j)a_i(\theta I_i - T) - R_i, \tag{2}$$

from which the indifference threshold with respect to investing or not investing depending on the signal is set. [to add, equilibrium]

Innovations in AI reasoning happen in between periods: after investors have decided ρ, the remainder R_{AI} determines the probability of a major breakthrough in reasoning ability. This is modelled as follows.[4] Two independent random draws from U(0, 1), $\pi_{\text{idea}}, \pi_{\text{obstacle}}$, correspond respectively to innovative ideas and to practical obstacles to innovation related to those ideas. The idea requires resources for implementation, and thus a technological advance only happens if the idea, once actually implemented, overcomes the barrier to innovation. Formally:

$$\phi = 1 - \max(0, \underbrace{\pi_{\text{idea}} * (1-\rho)}_{\text{Implemented idea}} - \pi_{\text{obstacle}}). \tag{3}$$

ϕ tapers off the noisiness to help the private signal get closer to $\theta + \eta$. Note that the only chance of a full shutdown of the added noise by the AI model - for example, through the concept of *artificial generalised intelligence*, is ruled out and would require all of the AI-related resources to the technologists only.

One important observation about the effect of AI on financial investments is consistent with a classical result in the global games literature (Morris and Shin (2002), Morris and Shin (2003)): the price ρ of AI resources has an outsized impact on outcomes by virtue of its public nature.

2.2 AI as a technique to read information

- Increased availability of data Veldkamp and Chung (2019) and lower cost across data pipeline Goldfarb and Tucker (2019). This facilitates the use

[3] A richer setting would see not only more investors, including atomic ones, but also have only the global AI resource expense be public, not its distribution to investors. The type of challenge it would bring to the current model includes for example a non-trivial correlation between the use of AI and the perceived signal. This interesting case demands a dedicated exposition and not further dealt with in this paper.

[4] Recall that ϕ determines the reasoning ability in a way that is orthogonal to model performance.

of new data, or data in a compound way, due to the "discovery" of new data by newer technologies Hirshleifer (1978).

- An early reference is Ranco et al. (2015). The idea is simple: new techniques not only process more data more effectively, but they also expand the envelope of data that can be analysed to look for signal.

2.3 Equilibrium in financial and AI investments

After the decisions to invest in AI is taken, the second stage involves an investment in the financial asset. This step resembles a traditional global game (Morris and Shin (2003)), but where players choose the precision of their own information as in, for example, Yang (2015), Szkup and Trevino (2021). The tendency of the game to a unique outcome, due to the limit uniqueness (D. M. Frankel, Morris, and Pauzner (2003)).

First, note there is exactly one value of $\alpha(R_i)$ that results in an minimally biased private signal.

Proposition 2.1 (AI use with minimal bias in private signal)**.** *There is only one specific value $\alpha^* = \alpha(R^*)$ for which the private signal is the closest to θ in expectation. The subscript is irrelevant because all investors are ex ante similar.*

Proof. The first order condition only holds for one value of $\alpha > 0$. Starting with the first derivative,

$$\frac{d}{d\alpha^*}(\eta + \phi e^{\lambda\alpha^*})\sigma/\alpha^* = 0$$

the expression can be manipulated to facilitate isolating α^* in the numerator to the left side:

$$\frac{\phi\lambda e^{\lambda\alpha^*}\sigma}{\alpha^*} - \frac{\phi e^{\lambda\alpha^*}\sigma}{(\alpha^*)^2} = \frac{\eta\sigma}{(\alpha^*)^2}.$$

Multiplying both sides by $(\alpha^*)^2$ obtains

$$\alpha^*\lambda\phi e^{\lambda\alpha^*}\sigma - \phi e^{\lambda\alpha^*}\sigma = \eta\sigma,$$

which is the same as

$$\phi e^{\lambda\alpha^*}(\lambda\alpha^* - 1) = \eta,$$

and thus if $\phi > 0$, the only possible solution with a positive value is $\alpha^* = 1/\lambda$.

The second derivative obtained by substituting this equality above is positive, confirming that α^* minimises the bias on the signal.

$$\frac{d^2}{d(1/\lambda)^2}(\eta+\phi e)\sigma\lambda = (\sigma\lambda^2\phi e + \sigma\lambda\phi e)\lambda^3$$

□

Proposition 2.1 highlights the problem with AI investment as a technology to process information: optimising on precision alone (lowering σ_i) exposes the investors to more biases in the signal at very high levels of technology adoption. Higher levels of R_i monotonically increase precision but there is only one level of R that minimises bias in information.

Note also that it seems to be a repetition of the classical bias-variance trade-off (BVTO) but it is in fact a different phenomenon. BVTO implies that more flexible and complex models would lead to lower bias and high out-of-sample variance, as more sophisticated models obtain a better fit to existing data at the risk of not generalising too well. The current setting shines a light on a different problem that incorporates economic and information- and game-theoretic elements: even if the model obtains lower variance by usefully increasing out-of-sample precision (real life examples include the ability to digest unstructured data such as text to improve signal pickup), the fact it *can* hallucinate and at the same time is increasingly trusted both by its practicality and precision, introduces uncertainty in the model.

3 Equilibrium

Note that similar to Szkup and Trevino (2021), the investment stage can resemble a global game, only with investors that are potentially heterogeneous on their private signals. So I follow standard practice in global games and find the equilibrium strategies based on a signal $x_i^*(R_i)$ that would lie at the investment indifference threshold for investor i:

$$A(R_i, x_i) = \mathbf{1}[x_i \geq x_i^*(R_i)].$$

Finding this threshold entails equating Equation 2 with zero under the investment scenario, ie $A(R_i, x_i) = 1$, and then solving for $x_i^*(R_i)$:

$$E[Pr(A_j(\theta)=1)\theta I_i | x_i = x_i^*, \theta \in [\underline{\theta}, \bar{\theta}]] + E[\theta I_i | x_i = x_i^*, \theta > \bar{\theta}] = T, \quad (4)$$

where $E[Pr(A_j(\theta)=1)]$ is the expected (by i) probability that j has invested in the asset given the fundamental. The first term on the left is the expected success payout in the intermediate fundamentals case, which requires coordination. The second term is the expected success in the good fundamentals scenario.

The equilibrium is due to Szkup and Trevino (2021), who extend the monotone supermodular games result from Van Zandt and Vives (2007) in games with unbounded utility functions. In particular, Szkup and Trevino (2021) show that there exist both a least and a greatest bounds in Bayesian Nash equilibra, and that these thresholds correspond to a univalent mapping to a unique outcome.

4 Reasoning

This section discusses the elements of ϕ that can be interpreted as an AI model's reasoning ability. It draws from Araujo (2024), where a more thorough discussion of rationality of AI models from an economics perspective can be found.

Recall from Equation 1 that ϕ outputs the additional noise components, except if the model is able to reason. At this point, ϕ is a gate that filters those noises.

Note that ϕ itself is not dependent on the performance of the AI. This is in line with compiling evidence that while the increasing power of AI affords it new abilities, including some that resemble reasoning, ultimately it is even questionable if a robust for of reasoning can be obtained by continuing to scale a technique that involves memorisation rather than actual abstract thinking (LeCun...)

5 Statistics

Szkup (2020) show that only the direct effect is important.

6 Open vs closed models

What is the influence, if any, of the possibility of investors to use exclusive, closed models to the equilibrium outcomes laid out above? This section relaxes the definition of α to allow for the possibility that investors spend some money in the first period to acquire or develop such models.

Assume that the development of a closed-model entails a cost $C > 0$ whereas the use of a public-knowledge open model is free (consistent with real life). In this case, then investors would choose the closed-model if $\alpha_i(R_i) > \alpha(R_i)$ and the final net payoff would still be positive even with the safe.

7 Operational risks (eg, cyber disruptions and AI vendor dependence)

Suppose now that α has a small but nonzero chance of being set to zero during the investment stage. Such a scenario would be akin to an operational risk incident, such as a cyber attack. Building on financial supervisors' work on risks from third party service providers, such as AI providers,[5] this section

[5]For example, the Basel Committee on Banking Supervision recently (2022) exorted banks to address risks related to concentration of third party service providers.

explores AI shutdown effects that are proportional to ρ.

Take Equation 1, but now assume that μ is a constant that always multiplies α. The constant goes to zero with probability ρ, representing an operational incident.

8 Supply chain disruptions

A shock during the investment phase that equivalently increases the price of the AI factors ρ or decreases their yield α.

9 Preliminary considerations[6]

- Introducing the use of AI to process information entails both an increase in precision, in line with past literature, but also changes that reflect hallucinations and other silent mistakes.
- Once investors use AI, its impact on prices is outsized. This is due to information on its adoption transpiring (eg, through the prices of AI resource) and also due to the spillovers that technology adoption have on innovation itself.
- The model is simple but sufficiently rich to capture an important set of equilibrium characteristics. For example, this model can help estimate the effects of hallucinations, closed vs open model mandates, operational risk issues and others.

10 Discussion

The idea that the market might overreact to the knowledge about deployment of AI by firms is not new (Morris and Shin (2002)).

More broadly, this model extends the work of Szkup and Trevino (2015b). That paper establishes important results with respect to the symmetric nature of the outcome of games that allow for information aquisition, and the relatively amenable conditions under which equilibrium is unique.

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[6] This section will become the conclusion section.

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