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

Douglas K. G. Araujo[1]

[1]Bank for International Settlements, douglas.araujo@bis.org

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.

1 Introduction

The increasing capabilities of large language models (LLM) and modern artificial intelligence (AI) systems more generally unlock useful new ways to transform data into actionable information, expanding the "data envelope" (Hirshlelfer (1971), Goldfarb and Tucker (2019)). These sophisticated models have been posited to be useful even for forecasting and stock trading (eg, Lopez-Lira and Tang (2023)), adding further momentum to the use of these technologies. Clearly, more advanced AI models are able to transform more data into information, improving the precision of a signal. But other key, specific features of AI as an information technology require new modelling tools that are not found in existing frameworks of endogenous information acquisition in incomplete games (eg, Hellwig and Veldkamp (2009), M. Yang (2015), Szkup and Trevino (2015b)). First, AI models can also output erroneous content that may be hard to identify,

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

such as seemingly-correct "hallucinations" (Alkaissi and McFarlane (2023), Ji et al. (2023)), an issue that is compounded by the inescrutable nature of these models. For example, LLMs might provide human-like answers that fail to correctly identify trivial aspects of tasks (Perez-Cruz and Shin (2024)). Second, the AI technology is still evolving at a fast pace (eg, J. Yang et al. (2023)), which itself might change the information acquisition calculation of agents as they expect a certain chance that current models will be nondecreasingly more powerful. In this paper, the AI resources not used by agents is made available to technologists, who then try to improve AI technology subject to resource availability. All of this on top of the usually modelled costs to acquire information, which in this case represent the limited AI-specific resources such as skilled labour force and adequate chips that are limited.

The main contribution of this paper is to set up a simple but flexible model of endogenous information acquisiton under incomplete information, subject to bias in the private signal (from the "AI hallucinations") and to stochastic technological breakthrough that improves the model's reasoning, tapering the hallucinations. Other than these AI-specific parameterisations, the model follows a standard information acquisition model that can be solved as a global game (Carlsson and Van Damme (1993), Morris and Shin (2003)), yielding a symmetric, unique equilibrium outcome. This baseline model is used to show that the equilibrium choices of AI resource take-up by investors facing a risky payoff are consistent with the level of AI that minimises bias in the private signal. In other words, investors invest the "right" amount in AI for their application at hand, even if the investment decision itself is risk- and not payoff-dominant (Harsanyi and Selten (1988)).

The baseline 2-investor game plays out in two stages. In the *AI investment* stage, each investor i chooses how much of their endowment E will be allocated to acquiring AI-related resources (eg, skilled practitioners, graphics processing unit chips - GPU) from a limited pool R. The remainder after the investors decide their AI investment is available to technologists, and will influence technological development: $R = R_{AI} + \sum_i R_i$. Next, the *financial investment* stage entails a binary investment decision on the remainder of the endowment, $I_i = E - R_i$. The payoff depends on an unobserved state θ and, for intermediate levels of the fundamental outcome, on coordination between investors. These decisions are taken after each investor observes a private signal that depends non-linearly on the level of AI investment: higher AI amounts increase precision in the private signal, but expose the investor to AI hallucinations. These latter elements are additive biases in the private signal that behave exponentially, like a "hockey stick" line, kicking off strongly at high levels of AI adoption. A final unknown component in the model is the degree of technological advance in between stages. Technologists take the remainer of the resources, R_{AI}, and use it to implement research ideas that are compared with obstacles. Whenever these are net positive, the hallucinations taper off. This represents for example advances in reasoning ability (Douglas K. G. Araujo (2024)) or in fine-tuning to make models.

A unique value of AI investment minimises the bias in the private signal, ie optimally balances the hallucination with the precision-increasing effects of greater investment in AI. Interestingly, even as the equilibrium definition is not conditional on an optimal first-stage allocation, this happens to be the value that is consistent with the second-stage equilibrium. 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 three of them. First, the baseline specification speaks to AI's ability to reason. One of the extensions, studying the effect of an eventual much-hyped artificial general intelligence (AGI), simply involves turning off the hallucination. The third extension addresses current policy and academic discussions around the wisedom of openly available versus closed models. Secondly, the model can be slightly adapted to study the potentially outsized effects of cyber security or other operational risk incidents, including issues related to AI vendor concentration.

1.1 Literature

This work relates to the literatures on information acquisition in incomplete information games, and on AI and data in finance. The class of global games models address incomplete information settings Carlsson and Van Damme (1993). Morris and Shin (2002), Morris and Shin (2003). A second stream of papers related to this work discuss endogenous information acquisition, similar to the current paper. **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.

Another stream of papers discusses **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. And a more specific line of works examines **AI in finance, including associated risks.** AI can read information better (Douglas Kiarelly Godoy Araujo et al. (n.d.), Douglas Kiarelly Godoy 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. Increased availability of data (Veldkamp and Chung (2019)) and lower cost across data pipeline (Goldfarb and Tucker (2019)). This facilitates the use of new data, or data in a compound way, due to the "discovery" of new data by newer technologies (**hirshleifer1978private?**). An early reference is Ranco et al. (2015). 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 Model

The model draws heavily from the setup in Szkup and Trevino (2021), with important additions that represent key features of AI as an information technology. 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 5 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 **?@sec-reasoning**). 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:

[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.

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

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 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]

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

[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.

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 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, M. 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:

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

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

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.

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

$\square$

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 $x_i^*(R_i)$:

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

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 Equilibrium

The equilibrium is found by backward induction. Starting with the financial investment stage, collect a vector $r = \{R_i, R_j, R_{AI}\}$ with the allocations of R. Investor strategies $A : \mathbf{R} \times [0,1]^3 \times (0,1] \to \{0,1\}$ map the private signal, the vector r and the AI reasoning ability ϕ to a binary investment decision, where 1 is associated with the investing choice.

Using the global games' threshold strategies and the uniqess of equilibrium outcomes due to Szkup and Trevino (2021) and Van Zandt and Vives (2007).

5 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.

6 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 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.

7 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.

8 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.

References

Alkaissi, Hussam, and Samy I McFarlane. 2023. “Artificial Hallucinations in ChatGPT: Implications in Scientific Writing.” *Cureus* 15 (2).

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

[6] This section will become the conclusion section.

Angeletos, G-M, and Chen Lian. 2016. "Incomplete Information in Macroeconomics: Accommodating Frictions in Coordination." In *Handbook of Macroeconomics*, 2:1065–1240. Elsevier.

Araujo, Douglas K. G. 2024. "Benchmarking Economic Reasoning in Artificial Intelligence Models."

Araujo, Douglas Kiarelly Godoy, Giuseppe Bruno, Juri Marcucci, Rafael Schmidt, and Bruno Tissot. n.d. "Data Science in Central Banking: Applications and Tools."

Araujo, Douglas Kiarelly Godoy, Sebastian Doerr, Leonardo Gambacorta, and Bruno Tissot. 2024. "Artificial Intelligence in Central Banking."

Basel Committee on Banking Supervision. 2022. "Newsletter on Third- and Fourth-Party Risk Management and Concentration Risk." Bank for International Settlements. https://www.bis.org.

Begenau, Juliane, Maryam Farboodi, and Laura Veldkamp. 2018. "Big Data in Finance and the Growth of Large Firms." *Journal of Monetary Economics* 97: 71–87.

Carlsson, Hans, and Eric Van Damme. 1993. "Global Games and Equilibrium Selection." *Econometrica: Journal of the Econometric Society*, 989–1018.

Colombo, Luca, Gianluca Femminis, and Alessandro Pavan. 2014. "Information Acquisition and Welfare." *The Review of Economic Studies* 81 (4): 1438–83.

Danielsson, Jon, Robert Macrae, and Andreas Uthemann. 2022. "Artificial Intelligence and Systemic Risk." *Journal of Banking & Finance* 140: 106290.

Farboodi, Maryam, Adrien Matray, Laura Veldkamp, and Venky Venkateswaran. 2022. "Where Has All the Data Gone?" *The Review of Financial Studies* 35 (7): 3101–38.

Frankel, David M, Stephen Morris, and Ady Pauzner. 2003. "Equilibrium Selection in Global Games with Strategic Complementarities." *Journal of Economic Theory* 108 (1): 1–44.

Frankel, David, and Ady Pauzner. 2000. "Resolving Indeterminacy in Dynamic Settings: The Role of Shocks*." *The Quarterly Journal of Economics* 115 (1): 285–304. https://doi.org/10.1162/003355300554746.

Goldfarb, Avi, and Catherine Tucker. 2019. "Digital Economics." *Journal of Economic Literature* 57 (1): 3–43.

Harsanyi, John C, and Reinhard Selten. 1988. "A General Theory of Equilibrium Selection in Games." *MIT Press Books* 1.

Hellwig, Christian, and Laura Veldkamp. 2009. "Knowing What Others Know: Coordination Motives in Information Acquisition." *The Review of Economic Studies* 76 (1): 223–51.

Hirshlelfer, Jack. 1971. "The Private and Social Value of Information and the Reward to Inventive Activity." *The American Economic Review* 61 (4): 561–74.

Ji, Ziwei, Nayeon Lee, Rita Frieske, Tiezheng Yu, Dan Su, Yan Xu, Etsuko Ishii, Ye Jin Bang, Andrea Madotto, and Pascale Fung. 2023. "Survey of Hallucination in Natural Language Generation." *ACM Computing Surveys* 55 (12): 1–38.

Korinek, Anton. 2023. "Generative AI for Economic Research: Use Cases and

Implications for Economists." *Journal of Economic Literature* 61 (4): 1281–1317. https://doi.org/10.1257/jel.20231736.

Lopez-Lira, Alejandro, and Yuehua Tang. 2023. "Can Chatgpt Forecast Stock Price Movements? Return Predictability and Large Language Models." *arXiv Preprint arXiv:2304.07619*.

Morris, Stephen, and HS Shin. 2003. "Global Games: Theory and Applications. Advances in Economics and Econometrics, m Dewatripont, l Hansen, and s Turnovsky." Cambridge University Press, NY.

Morris, Stephen, and Hyun Song Shin. 2002. "Social Value of Public Information." *American Economic Review* 92 (5): 1521–34.

Perez-Cruz, Fernando, and Hyun Song Shin. 2024. "Testing the Cognitive Limits of Large Language Models." Bank for International Settlements.

Ranco, Gabriele, Darko Aleksovski, Guido Caldarelli, Miha Grčar, and Igor Mozetič. 2015. "The Effects of Twitter Sentiment on Stock Price Returns." *PloS One* 10 (9): e0138441.

Reshidi, Pëllumb, Alessandro Lizzeri, Leeat Yariv, Jimmy H Chan, and Wing Suen. 2021. "Individual and Collective Information Acquisition: An Experimental Study." National Bureau of Economic Research.

Szkup, Michal, and Isabel Trevino. 2015a. "Information Acquisition and Transparency in Global Games." *Journal of Economic Theory* 160: 387–428.

———. 2015b. "Information Acquisition in Global Games of Regime Change." *Journal of Economic Theory* 160: 387–428.

———. 2021. "Information Acquisition and Self-Selection in Coordination Games." mimeo.

Van Zandt, Timothy, and Xavier Vives. 2007. "Monotone Equilibria in Bayesian Games of Strategic Complementarities." *Journal of Economic Theory* 134 (1): 339–60.

Veldkamp, Laura, and Cindy Chung. 2019. "Data and the Aggregate Economy." *Journal of Economic Literature*.

Yang, Jingfeng, Hongye Jin, Ruixiang Tang, Xiaotian Han, Qizhang Feng, Haoming Jiang, Bing Yin, and Xia Hu. 2023. "Harnessing the Power of LLMs in Practice: A Survey on Chatgpt and Beyond." *arXiv Preprint arXiv:2304.13712*.

Yang, Ming. 2015. "Coordination with Flexible Information Acquisition." *Journal of Economic Theory* 158: 721–38.