Chatbots, Investor Coordination, and Financial Fragility

and Financial Market Fragility

Jeanine Baumert

November 2, 2026

Abstract

This paper studies the adoption of AI investment tools in a noisy rational-expectations market. Retail investors can adopt an AI technology that pools the positions disclosed by its users and thereby provides information about aggregate liquidity conditions, which helps them interpret market prices. The technology contains no information about fundamentals. Adoption affects equilibrium trading and price informativeness, so the private value of the technology depends on its market-wide use. I characterize the competitive linear rational-expectations equilibrium and the associated adoption incentives. Because the AI signal multiplies the precision of the information that the price contains, rather than adding to it as a signal about fundamentals would, its value can rise with price informativeness. Greater adoption makes prices more informative, so AI adoption can be a strategic complement at stable trading equilibria, including unique ones. Adoption can then have multiple equilibria, and small changes in the cost of the technology or in expectations about its use can produce discrete changes in adoption and price informativeness.

JEL Classifications: D82, D83, G12, G14

Keywords: Artificial Intelligence, Learning from Prices, Information Acquisition, Strategic Complementarity, Price Informativeness, Financial Fragility

1 Introduction

Retail investors increasingly consult AI assistants before they trade. In 2026, several of the largest retail brokers in the United States and Europe opened their platforms to general-purpose assistants such as ChatGPT and Claude, so that an assistant observes a client's positions, open orders, and trade history and, on some platforms, proposes trades for her approval.[1] One survey puts the share of retail investors who use AI tools to select or adjust their investments at roughly one in five, up from about one in eight a year earlier,[2] and financial-stability authorities have identified correlated behavior among investors who rely on the same tools as a risk (Financial Stability Board, 2024; Leitner, Singh, van der Kraaij, and Zsámboki, 2024). What can such an assistant tell an investor? The models behind these assistants are trained on past, public data: historical prices, company filings, news, and research reports. In an efficient market, this information is already reflected in prices (Fama, 1970). In a rational expectations equilibrium, investors moreover understand how prices relate to fundamentals and condition on the price when they trade (Grossman, 1976; Grossman and Stiglitz, 1980). An AI that only learns from past, public data may help an investor to process public information, but it cannot give her a signal about the asset's payoff that is not already reflected in the price.

There is, however, one kind of information that an AI assistant obtains through its use and that the price does not contain: what its users disclose about themselves. In conversations with an assistant, investors describe their portfolios, their cash needs, and the trades they are considering, and increasingly the assistant observes their positions directly. A service with many users can pool these disclosures. Idiosyncratic components average out, and the service learns how much its users, as a group, need to buy or sell for reasons that are unrelated to the asset's payoff. In the language of the noisy rational expectations literature, the service learns about the aggregate endowment shock, which is part of the random supply of the asset. The

[1] Interactive Brokers, press release, June 1, 2026, https://www.interactivebrokers.com/en/general/about/mediaRelations/6-1-26.php; Scalable Capital, press release, August 25, 2026, https://nl.scalable.capital/newsroom/agentic-investing; eToro, press release, October 8, 2026, https://www.etoro.com/news-and-analysis/press-releases/your-ai-already-runs-your-day-now-it-knows-your-portfolio/. Section 2 gives details.

[2] eToro, "Retail Investors Flock to AI Tools, with Usage Up 46% in One Year," October 1, 2025, https://www.etoro.com/news-and-analysis/etoro-updates/retail-investors-flock-to-ai-tools-with-usage-up-46-in-one-year/.

price is a noisy signal of the payoff because it also moves with supply. Information about the endowment shock does not forecast the payoff, but it allows an investor to remove part of the noise from the price.

This observation does not contradict the logic of Grossman and Stiglitz (1980); it applies that logic to a different object. In their model, noise in supply is what prevents the price from revealing all information and what therefore makes private information about the payoff worth acquiring. Here the acquirable information is information about the noise itself. Such information is useful only in combination with the price. This changes how its value responds to the information in the price, and it is what makes the economics of AI signals different from the economics of payoff signals. This paper studies the value of such AI signals, the incentives to acquire them, and their effects on prices. The main result is that the acquisition of AI signals can be a strategic complement at stable trading equilibria: the more investors use AI, the more valuable AI becomes for each of them. It can produce multiple stable equilibria in the market for AI.

I study a competitive noisy rational expectations market in the tradition of Grossman and Stiglitz (1980), Hellwig (1980), and Diamond and Verrecchia (1981). Investors have CARA preferences and receive endowments of the risky asset with an aggregate and an idiosyncratic component. The aggregate endowment shock is part of the supply of the asset, and each investor's own endowment is a private signal of it. Investors therefore learn privately from the price: each one uses her endowment to correct the price for the endowment shock, so that investors with different endowments draw different inferences from the same price. Before trading, retail investors decide whether to use an AI service, which returns to each user a second noisy signal of the aggregate endowment shock. The precision of this signal does not depend on how many investors use the service, ruling out an exogenously imposed network effect. Moreover, the signal contains no information about the payoff.

The mechanism has three parts. The first is what the AI signal does for an individual investor. A low price can reflect bad news about the payoff or a large supply of the asset, and the price alone does not reveal which. The AI signal tells an investor about one part of this supply, the aggregate endowment shock. If she learns that the shock is large, she attributes less of a low price to bad news. The signal thus lets her remove part of the noise from the

price, and this is the only way in which it is useful: on its own, it says nothing about the payoff.

The second part is how the value of such a signal depends on the price. A signal about the payoff adds a fixed amount of information, whatever the price reveals, so it is worth less the more the price already reveals. The AI signal instead removes a share of the noise in the price, so the precision it adds is proportional to the precision of the price itself: it is worth more when the price is more informative.

The third part is the feedback through the market. In the standard model, others' acquisition of information makes the price more informative, and a more informative price lowers the value of a signal about the payoff; this is why information acquisition is a strategic substitute (Grossman and Stiglitz, 1980; Verrecchia, 1982). Here, others' adoption also makes the price more informative: AI users buy more when a low price reflects the endowment shock rather than bad news, so the shock moves the price less relative to fundamentals, and, at a stable trading equilibrium, the price becomes more informative for every investor. By the second part, this raises the value of the AI signal. Adoption can therefore be a strategic complement: the more investors use AI, the more each of them values it.

The complementarity has a limit, and it comes from noise trading. The AI removes the endowment shock from the price but not noise trading, and the more informative the price, the larger the share of noise trading in the noise that remains. Close to the maximal informativeness that noise trading permits, further adoption improves the price information of non-users more than that of AI users, and the value of AI falls. I give the exact condition under which adoption is a complement at a stable trading equilibrium, and a sufficient condition on primitives alone, which does not require the trading equilibrium to be unique. The condition is harder to satisfy the more precise the AI: a user of a perfectly precise AI already interprets the price as well as noise trading allows, so others' adoption cannot help her. Since a very imprecise AI is worth little, the complementarity matters most for an AI of intermediate precision. It also requires that informed trading does not fully adjust to adoption.

The complementarity in adoption is noteworthy because complementarity in information acquisition is difficult to obtain in financial markets. For a payoff signal, it would require that

others' acquisition make the price less informative, which in the standard models happens only at unstable trading equilibria. Manzano and Vives (2011) establish this in a model in which investors learn privately from the price through their endowments, as they do here: acquisition is a complement only at equilibria at which the aggregate best response is steeper than one, which are unstable. Ganguli and Yang (2009) find that acquisition can be a complement when traders can buy a signal about supply together with a signal about the payoff. Their setting differs from the one here, in which retail investors have no information about the payoff to acquire and the information about supply available to them is what an AI service pools from the disclosures of investors like themselves. Otherwise, the literature has obtained complementarities only by adding further ingredients, such as short horizons, non-normal payoffs, increasing returns in the production of information, coordination motives, relative wealth concerns, ambiguity aversion, multiple fundamentals, or feedback from prices to real decisions (Froot, Scharfstein, and Stein, 1992; Barlevy and Veronesi, 2000; Veldkamp, 2006; Hellwig and Veldkamp, 2009; García and Strobl, 2011; Mele and Sangiorgi, 2015; Goldstein and Yang, 2015; Dow, Goldstein, and Guembel, 2017). None of these is needed here: the complementarity arises in the plain CARA-normal model, at stable trading equilibria, whether or not the trading equilibrium is unique, from the kind of information that the AI provides, information about supply alone.

With complementarity, adoption becomes a coordination problem. If investors expect few others to use AI, they expect a less informative price; interpreting it better is then worth less than the cost of AI, and few adopt. If they expect many others to use AI, the price is more informative, interpreting it better is worth the cost, and many adopt. For a range of costs, both expectations are self-fulfilling. This multiplicity is in the market for AI and does not rely on multiplicity in the asset market. A simple sufficient condition for the trading equilibrium to be unique at every adoption rate is that the variance of noise trading be large relative to the mass and signal precision of informed investors and to investors' risk tolerance. Under this condition, if adoption is a complement when nobody uses AI, every common cost of AI between its value when nobody uses it and its peak value supports two stable equilibria, one without adoption and one with positive adoption. Under an analogous condition, information about the payoff cannot generate such multiplicity.

Under the same condition, adoption changes prices in three ways. First, the endowment shock moves the price less relative to fundamentals, because AI users buy more when it depresses the price; the price becomes more informative. Second, the price responds more strongly to fundamentals: investors learn more from the price, so their expectations, and with them the price, track the payoff more closely. Third, noise trading moves the price more, in the same proportion as fundamentals. Nobody has information about noise trading, and the more investors rely on the price as a signal of the payoff, the less they buy when it falls, so the price must fall further to clear a given sale by noise traders. The market thus becomes more informative but, in the sense that the flows the AI does not observe move the price more, also more fragile. This does not come from errors of the AI, because each user's error is her own and averages out; it comes from the market's greater reliance on its price.

When the variance of noise trading is small, the trading stage itself can have several equilibria, because private information about supply can make price informativeness self-fulfilling, as in Ganguli and Yang (2009) and Manzano and Vives (2011). AI then works in both directions. It can create multiple trading equilibria where there is only one without AI: AI users trade more on their supply information than non-users, which can make an informative price self-fulfilling. A sufficiently precise AI held by enough investors removes the multiplicity: its users trade on their supply information almost regardless of what they expect the price to reveal, which rules out a self-fulfilling uninformative price. A sufficiently precise AI held by enough investors removes the multiplicity: its users trade on their supply information almost regardless of what they expect the price to reveal, which rules out a self-fulfilling uninformative price; in the limit in which the AI reveals the endowment shock, a small minority of investors suffices. Because the precision of the AI signal is what improves when the service improves, as users link their brokerage accounts, disclose more of their trading needs, and the models themselves improve, technological progress makes the asset market less prone to multiplicity, whereas restrictions on the data that the service may use, which lower the precision of its signal, work in the opposite direction.

Related Literature

The paper builds on the noisy rational expectations literature on information aggregation and learning from prices (Grossman, 1976; Hellwig, 1980; Diamond and Verrecchia, 1981; Allen, Morris, and Shin, 2006; Ottaviani and Sørensen, 2015; Andrei, Cujean, and Wilson, 2023); Vives (2008) provides a synthesis. Closest are Ganguli and Yang (2009) and Manzano and Vives (2011). In both, investors have private information about supply and therefore learn privately from the price, which creates a strategic complementarity in the use of information and can generate multiple trading equilibria. Manzano and Vives (2011) show that in economies with private learning, complementarity in the acquisition of payoff information arises only at unstable equilibria, and that such acquisition is a strategic substitute at stable equilibria. In Ganguli and Yang (2009), traders can buy information about the payoff and about supply together, and acquisition can be a complement. Their setting differs from the one here, in which retail investors have no information about the payoff to acquire and the information about supply available to them is what an AI service pools from the disclosures of investors like themselves. The economic force is related to Farboodi and Veldkamp (2020), in whose model data about other investors' demand help to extract the signal from prices, so that their value rises as prices become more informative, and to Marmora and Rytchkov (2018), who show that learning about noise raises price informativeness. Relative to these papers, I give an exact condition for the complementarity in a model with private learning from prices, separate it from the complementarity in the use of information that noise trading disciplines, and show that it can produce multiple stable equilibria in the market for information even when the asset market has a unique and stable equilibrium.

The paper also contributes to the literature on complementarities in information acquisition cited above, and to the literature on financial market fragility, which Goldstein, Huang, and Yang (2025) organize around amplification and multiplicity. Allen and Gale (1994, 2004) and Gennotte and Leland (1990) study fragility arising from limited participation and scarce liquidity and from portfolio-insurance hedging; Gennaioli, Shleifer, and Vishny (2012) from the widespread adoption of a financial innovation whose risks are neglected; Ahnert and Kakhbod (2017) from endogenous information choice in a coordination setting; and Wagner (2010, 2011), Ahnert and Georg (2018), and Cipriani and Guarino (2014) from institutions,

information sources, and herding that make market participants act alike. Here the innovation is adopted with full understanding of its risks and its errors diversify away; fragility arises from the market's greater reliance on the price, which amplifies the flows that the AI does not observe, and the coordination problem that the complementarity in adoption creates makes these changes discrete. Relative to models of runs with dispersed information (Goldstein and Pauzner, 2005; Rochet and Vives, 2004), the dispersion that could select a unique equilibrium here is in adoption costs, and it must be comparable to the variation in the value of AI across adoption rates to do so.

A growing literature studies artificial intelligence in financial markets. Cartea, Colliard, Foucault, Hoffmann, Graumans, and Sigaux (2026) survey it and organize it around the idea that AI raises the productivity of data in the production of information. They stress that the effect of AI on price informativeness depends on the kind of information it produces. AI can be used to discover information about fundamentals, or to infer other traders' fundamental information from market data, which weakens the incentive to discover such information (Farboodi and Veldkamp, 2020; Yang and Zhu, 2020; Weller, 2018). The AI in this paper is closer to the second use, with a retail rather than a professional user: it discovers nothing about fundamentals, but by telling its users about the endowment component of supply, it helps them infer from the price what informed investors know, and at stable trading equilibria it lowers the value of acquiring information about fundamentals (Proposition 4(iii)). On financial stability, the survey weighs the concern that common models and data lead investors to act alike against a counterargument based on Grossman and Stiglitz (1980): the value of a signal that many investors share dissipates, which gives investors an incentive to use different models and data. The AI signal here is an exception to this counterargument, because its value can rise with the number of investors who use it: what it is used for, interpreting the price, can become more valuable as the price becomes more informative. In most of the literature, AI is used by professional traders or is the prediction technology. Dou, Goldstein, and Ji (2025, 2026) study AI speculators that learn to collude and to coordinate on bubbles; Colliard, Foucault, and Lovo (forthcoming) find that reinforcement-learning market makers learn to compete only partially and do not reach competitive spreads, and Cartea, Chang, and Penalva (2022) study algorithmic collusion in electronic markets; Kelly,

Malamud, and Zhou (2024) and Leippold, Wang, and Zhou (2022) study machine learning in return prediction; Daníelsson, Macrae, and Uthemann (2022), the Financial Stability Board (2024), and Leitner et al. (2024) discuss systemic risk from the concentration of models. Here AI is a retail-facing conversational tool, its information is about supply rather than fundamentals, and the only strategic interaction is through the price. On the retail side, the paper connects to the evidence on retail order flow (Boehmer, Jones, Zhang, and Zhang, 2021; Barber, Huang, Odean, and Schwarz, 2022; Welch, 2022), to the economics of financial advice and robo-advice (Bolton, Freixas, and Shapiro, 2007; Inderst and Ottaviani, 2009; Bhattacharya, Hackethal, Kaesler, Loos, and Meyer, 2012; D'Acunto, Prabhala, and Rossi, 2019; Rossi and Utkus, 2024; Greig, Ramadorai, Rossi, Utkus, and Walther, 2025), and to early evidence on retail investors' use of large language models (Bauer, Damm, Hett, and Pelizzon, 2026; Blankespoor, Croom, and Grant, 2026; Fedyk, Kakhbod, Li, and Malmendier, 2026; He, 2026). Unlike the information vendor in Admati and Pfleiderer (1986, 1990), the AI service pools its users' own data and returns information about supply rather than about the payoff. Finally, the paper relates to work on price informativeness and its measurement (Bai, Philippon, and Savov, 2016; Dávila and Parlatore, 2023; Kacperczyk, Nosal, and Sundaresan, 2025) and on what prices reveal about informed trading and liquidity (Rindi, 2008; Foucault and Gehrig, 2008; Collin-Dufresne and Fos, 2015).

The remainder of the paper proceeds as follows. Section 2 describes the institutional background. Section 3 presents the model. Section 4 characterizes the trading equilibrium for a given adoption rate, its uniqueness and multiplicity, and its stability. Section 5 studies how adoption changes price informativeness and the price impact of shocks. Section 6 contains the main results on strategic complementarity and multiple equilibria in the acquisition of AI signals. Section 7 discusses empirical implications, Section 8 policy implications, and Section 9 limitations. Section 10 concludes. Derivations and proofs are in the Appendix.

2 Institutional Background

This section describes the environment that the model is meant to capture: the AI assistants available to retail investors, their usage, the information that users disclose to them, and the

concerns of policymakers.

2.1 AI Assistants in Retail Brokerage

The first wave of AI in retail brokerage was closed and advisory. Public.com announced a GPT-4-based research assistant for its app in May 2023;[3] Robinhood announced *Cortex*, an AI tool that summarizes the news affecting a stock, in March 2025;[4] Interactive Brokers launched *Ask IBKR*, which answers natural-language questions about the client's own holdings, performance, and cash flows, in October 2025;[5] Charles Schwab's *Charley*, rolling out from October 2026, answers questions about balances, positions, and statements and can act on account settings.[6] In China, Ant Group's assistant inside Alipay reported seventy million monthly active users by August 2024.[7]

The second wave is open and agentic, and it is the relevant one for the model. Instead of building a chatbot, brokers now let clients connect the general-purpose assistant they already use. Robinhood opened an agentic-trading beta in May 2026 in which a user's own AI agent, connected through a standard protocol, has read access to her portfolio and executes stock trades from a dedicated agent account.[8] Interactive Brokers followed in June 2026 with a certified connector to Claude, with the ChatGPT, Gemini, and Grok integrations "currently undergoing the certification process": the assistant accesses positions, open orders, trade

[3]Public, "Introducing Alpha: Your Investing Co-Pilot," Public Stories blog, May 17, 2023, https://medium.com/the-public-blog/introducing-alpha-your-investing-co-pilot-c536b740e907.

[4]Robinhood, "Introducing Robinhood Strategies, Robinhood Banking, and Robinhood Cortex," Robinhood Newsroom, March 27, 2025, https://robinhood.com/us/en/newsroom/introducing-strategies-banking-and-cortex.

[5]Interactive Brokers, "Interactive Brokers Launches Ask IBKR: AI Tool Delivers Instant Portfolio Answers," press release, October 15, 2025, https://www.businesswire.com/news/home/20251015991473/en/Interactive-Brokers-Launches-Ask-IBKR-AI-Tool-Delivers-Instant-Portfolio-Answers.

[6]Charles Schwab, "Meet Charley, Schwab's New AI-Powered Assistant Designed to Help Clients Get Answers and Take Action," press release, September 30, 2026, https://pressroom.aboutschwab.com/press-releases/press-release/2026/Meet-Charley-Schwabs-New-AI-Powered-Assistant-Designed-to-Help-Clients-Get-Answers-and-Take-Action/default.aspx.

[7]Ant Group, "Ant Group Unveils AI Financial Manager at Shanghai's INCLUSION Conference," press release, September 6, 2024, https://www.businesswire.com/news/home/20240905719583/en/Ant-Group-Unveils-AI-Financial-Manager-at-Shanghais-INCLUSION-Conference.

[8]Robinhood, "Robinhood Is Now Open to Agents," Robinhood Newsroom, May 27, 2026, https://robinhood.com/us/en/newsroom/robinhood-is-now-open-to-agents/; Robinhood, "Onboarding an External Agent," Robinhood Support, accessed October 30, 2026, https://robinhood.com/us/en/support/articles/agentic-trading-overview/; Ivan Mehta, "Robinhood Now Lets Your AI Agents Trade Stocks," TechCrunch, May 27, 2026, https://techcrunch.com/2026/05/27/robinhood-now-lets-your-ai-agents-trade-stocks/.

history, and margin information, and generates trade instructions that the client approves one by one.[9] In August 2026, Scalable Capital, based in Munich, with more than a million clients and over 60 billion euros in assets, became, by its own account, the first bank in Europe to open its platform to "all major AI assistants," which can access the portfolio, run diversification and scenario analyses, and place orders and savings plans subject to the user's confirmation.[10] eToro, with forty million registered users,[11] launched connectors for Claude, ChatGPT, and Grok in October 2026, through which users can ask about "their actual holdings, positions, balances and performance."[12] Perplexity and Plaid let users link brokerage accounts so that the assistant receives holdings, transactions, and balances directly;[13] Google Finance lets users build a tracked portfolio by describing their holdings in plain language.[14]

Two features of this second wave map directly into the model. First, the assistant is a *shared* service: the same handful of models serve millions of retail investors across brokers, so that what these users disclose is held by a few providers. The announcements above document access to individual accounts, and the consumer terms discussed below document that conversations can be used to improve models; whether providers aggregate positions across users is not public, and the model assumes that they can. Second, what the assistant learns about each user is her *position*: holdings, cash, open orders, the trade she is contemplating. It is not a signal about the firm. Fintech has mostly meant new information technology in

[9] Interactive Brokers, "Interactive Brokers Integrates AI into Client Portfolios—Informed by Agentic Technology, Controlled by the Client," press release, June 1, 2026, https://www.interactivebrokers.com/en/general/about/mediaRelations/6-1-26.php. ChatGPT and Grok were added three weeks later: Interactive Brokers, "Interactive Brokers Expands AI Integration Capabilities—Adding ChatGPT and Grok to Its Growing Suite of Agentic Trading Tools," press release, June 22, 2026, https://www.interactivebrokers.com/en/general/about/mediaRelations/6-22-26.php.

[10] Scalable Capital, "Scalable Capital Becomes First Bank in Europe to Open Platform to AI Assistants via Agentic Investing," press release, August 25, 2026, https://nl.scalable.capital/newsroom/agentic-investing.

[11] eToro, "eToro Group Reports Selected May Business Metrics," press release, June 8, 2026, https://www.etoro.com/news-and-analysis/press-releases/etoro-group-reports-selected-may-business-metrics/.

[12] eToro, "Your AI Already Runs Your Day. Now It Knows Your Portfolio," press release, October 8, 2026, https://www.etoro.com/news-and-analysis/press-releases/your-ai-already-runs-your-day-now-it-knows-your-portfolio/.

[13] Kathleen McGuirk, "How Plaid Powers Intelligent Finance with Perplexity," Plaid blog, March 11, 2026, https://plaid.com/blog/powering-intellligent-finance-with-perplexity/.

[14] Barine Tee, "Our Latest Google Finance Upgrades, Including a New App," The Keyword (Google blog), June 25, 2026, https://blog.google/products-and-platforms/products/search/google-finance-updates-june-2026/.

the hands of intermediaries (Boot, Hoffmann, Laeven, and Ratnovski, 2021), and technology adoption by one group of traders changing price formation for everyone has precedents, most recently in high-frequency liquidity provision (Menkveld, 2013; Menkveld and Zoican, 2017); the difference here is that the technology is on the retail side and its information concerns the users themselves.

2.2 Usage and Disclosure

Usage has grown from a low base. The FINRA Investor Education Foundation (2024) found that only five percent of U.S. adults reported using AI for information when making financial decisions; eToro's survey of eleven thousand retail investors in thirteen countries (fieldwork August 2025) found that nineteen percent use AI tools to pick or alter investments in their portfolios, up from thirteen percent a year earlier, and thirty-nine percent said they were open to adopting them;[15] and a survey of a representative sample of roughly one thousand U.S. adults by Choukhmane, de Silva, Lin, and Akuzawa (2026) found that forty-eight percent had used an AI tool for financial advice or information in the previous three months. Among U.S. adults who have used generative AI, two thirds say they have used it to seek financial advice, and among those, a third ask about investing in the stock market.[16]

Retail investors have always followed shared sources, from brokers' advice, whose take-up is limited even when it is unbiased (Bhattacharya, Hackethal, Kaesler, Loos, and Meyer, 2012), to finfluencers (Gerritsen and de Regt, 2025), and their processing of information is subject to well-documented frictions (Laudenbach, Ungeheuer, and Weber, 2023). What matters for the model is less how many ask than what they say when they ask. Choukhmane et al. (2026) collected users' free-text prompts: when describing their financial situation, sixty-five percent mention specific figures and a third mention dollar amounts, and investment prompts are dominated by the user's assets and risk preferences rather than by tickers. This is the information structure of Section 3: retail users have nothing to disclose about

[15] eToro, "Retail Investors Flock to AI Tools, with Usage Up 46% in One Year," Retail Investor Beat, October 1, 2025, https://www.etoro.com/news-and-analysis/etoro-updates/retail-investors-flock-to-ai-tools-with-usage-up-46-in-one-year/.

[16] Intuit Credit Karma, "The Rise of Fin-AI: Why Americans Are Trusting Generative AI with Their Wallets," September 2, 2025, https://www.creditkarma.com/about/commentary/the-rise-of-fin-ai-why-americans-are-trusting-generative-ai-with-their-wallets.

fundamentals, but they know, and state, their own positions and needs. Three features of the services make this disclosure persistent and potentially poolable. Assistants now remember across sessions: since April 2025 ChatGPT can reference all of a paying user's past conversations.[17] Consumer ChatGPT conversations are used to improve OpenAI's models unless users switch the corresponding setting off,[18] and Anthropic's consumer terms of August 2025 ask Free, Pro, and Max users to choose whether their conversations are used for training, with retention extended to five years for those who allow it.[19] And with linked accounts the disclosure is no longer a matter of what the user types. Users trade their data for a service, as in the economics of platform data (Ahnert, Hoffmann, and Monnet, 2025), and the service's informational advantage is the aggregate of what they hand over, much as fintech lenders' advantage is the pooled data of their users (Hau, Huang, Lin, Shan, Sheng, and Wei, 2024). Even accidental disclosure of positions affects prices (Galema and Gerritsen, 2019); here disclosure is systematic.

2.3 The Information Content of the AI Signal

The assumptions of the model follow from what the assistant can and cannot know.

About the *payoff*, the assistant knows the public record. Large language models process filings and news effectively (Eisfeldt and Schubert, 2025, survey the evidence), but the public record is already reflected in prices, and whatever predictability a model extracts from it should decay as more investors use the same model; Lopez-Lira and Tang (2026) find that the returns to trading on ChatGPT's forecasts decline as adoption of large language models rises. I therefore give the AI no information about the payoff.

About *supply*, the assistant knows what its users tell it, and across many users this is a measurement of the aggregate component of their trading needs. Pooling participants' positions to learn an aggregate has a long institutional history (Börner and Hatfield, 2017);

[17] OpenAI, "Memory and New Controls for ChatGPT," update of April 10, 2025, `https://openai.com/index/memory-and-new-controls-for-chatgpt/`.

[18] OpenAI Help Center, "What If I Want to Keep My History On but Disable Model Training?," accessed October 30, 2026, `https://help.openai.com/en/articles/8983130-what-if-i-want-to-keep-my-history-on-but-disable-model-training`.

[19] Anthropic, "Updates to Consumer Terms and Privacy Policy," August 28, 2025, `https://www.anthropic.com/news/updates-to-our-consumer-terms`.

here the pool is formed through conversations. I model the pooled signal as the aggregate endowment shock plus a user-specific error, with no error common to all users. The latter is a simplification that isolates the mechanism; Section 9 discusses common errors.

About the *flows it does not see*, the assistant knows nothing. Institutional rebalancing, index reconstitution, retail flow routed through brokers that are not connected, and the users of other assistants all trade in the same market. This is the noise trading of the model, and the asymmetry between the flow that the assistant measures and the flow that it does not is the source of the fragility results.

2.4 Policy Concerns

Financial-stability authorities have focused less on the quality of the advice that individual investors receive than on the possibility that many investors who rely on the same tool act alike. The Financial Stability Board (2024) lists market correlations among its four AI vulnerabilities; the International Monetary Fund (2024) warns that AI may "increase turnover and asset correlations" and that volatility under stress may rise "if trading strategies of AI models all respond to a shock in a similar manner"; the European Central Bank's special feature on AI states that "extensive use of AI by retail investors may result in large and similar shifts in retail trading patterns" (Leitner, Singh, van der Kraaij, and Zsámboki, 2024); and the Bank of England (2025) notes that herding and market concentration was the top risk cited in recent IMF outreach. Conduct regulators have so far relied on existing rules: ESMA (2024) reminded firms that the organisational and suitability requirements of MiFID II apply when AI is used in retail investment services, and FINRA (2024) that its technology-neutral rules, including those on supervision, apply to generative AI; the SEC's 2023 proposal on predictive data analytics was withdrawn in June 2025;[20] and the chief executive of the FCA has told Parliament that a model that provides information but no individualised recommendation leading to a transaction "does not fall fully within the regulated perimeter" (Rathi, 2026). Experimental and field evidence is beginning to accumulate. Bauer, Damm, Hett, and Pelizzon (2026) find that LLM assistants expand stock market participation while re-

[20] Securities and Exchange Commission, "Withdrawal of Proposed Regulatory Actions," Release No. 33-11377, *Federal Register* 90:25531–33, June 17, 2025, `https://www.federalregister.gov/documents/2025/06/17/2025-11110/withdrawal-of-proposed-regulatory-actions`.

inforcing confirmation-seeking; He (2026) uses unexpected ChatGPT outages and finds that retail order flow is more correlated within and across stocks when the assistant is available, and that price impact is higher (He, 2026, Section 4.4).

The model addresses this concern from a different angle. The correlated behavior that AI induces in the model is not an error that users share; every AI user's error is her own. It is the rational response of many investors to the same improvement in their interpretation of the price, and it makes the market more informative and, at the same time, more sensitive to the flows that the tool does not observe.

3 Model

The model is a competitive noisy rational expectations market in the tradition of Grossman and Stiglitz (1980), Hellwig (1980), and Diamond and Verrecchia (1981), with the endowment-shock structure of Manzano and Vives (2011) and one addition, an AI service that retail investors can adopt. There are three dates. At date 0, retail investors decide whether to use the AI service. At date 1, investors receive their private information and trade a risky asset against a riskless asset in a competitive market. At date 2, the risky asset pays off and investors consume.

3.1 Assets and Investors

The riskless asset is the numeraire and has a zero net return. The risky asset pays

$$v \sim \mathcal{N}(0, \tau_v^{-1}) \tag{1}$$

at date 2. Throughout, τ_x denotes the precision of a random variable x. All shocks are normally distributed and mutually independent, and idiosyncratic shocks are independent and identically distributed across investors.

Investors. There is a continuum of investors $i \in [0, 1]$ of two types. A set of investors of mass α is informed: they observe a private signal about the payoff (Section 3.3). They

stand for professional investors that research the asset, such as hedge funds and active asset managers. The remaining investors, of mass $1 - \alpha$, are retail investors. They have no information about the payoff, but they can use the AI service at date 0; informed investors cannot. The mass α is fixed in the baseline; Section 6.5 lets it respond to the value of information.

Endowments. Investor i is endowed with

$$u_i = u + \nu_i, \qquad u \sim \mathcal{N}(0, \tau_u^{-1}), \qquad \nu_i \sim \mathcal{N}(0, \tau_\nu^{-1}), \tag{2}$$

units of the risky asset. I adopt the convention that the law of large numbers holds for a continuum of independent and identically distributed variables (Vives, 2008), so that $\int_0^1 \nu_i \, di = 0$ almost surely. The same holds for the average over any set of investors of positive mass and for the idiosyncratic signal errors introduced below. Endowment shocks are the standard device for giving investors reasons to trade that are unrelated to information about the payoff (Diamond and Verrecchia, 1981; Vives, 2008). They stand for liquidity needs, for positions in other assets whose returns are correlated with the payoff, or for portfolio adjustments that investors want to make for reasons of their own; The aggregate endowment shock u is part of the supply of the asset that investors hold in equilibrium. Because each investor's endowment is correlated with it, each investor has private information about supply, as in Ganguli and Yang (2009) and Manzano and Vives (2011). I refer to an investor's information about u as her supply information.

Noise traders. Noise traders supply $\omega \sim \mathcal{N}(0, \tau_\omega^{-1})$ units of the risky asset. Nobody observes ω or a signal of it. Noise trading stands for flows that the AI service does not observe, such as institutional rebalancing or retail flows routed through other platforms. The aggregate supply that investors hold in equilibrium is therefore $u + \omega$.

3.2 Preferences

Investors have CARA utility $-\exp(-\gamma W)$ over terminal wealth W, with a common coefficient of absolute risk aversion $\gamma > 0$. Let x_i denote investor i's net purchase of the risky asset at

price p, so that she holds $u_i + x_i$ units after trading. With initial cash normalized to zero, her terminal wealth before the cost of the AI service is

$$W_i = u_i v + x_i(v - p). \tag{3}$$

3.3 Information Structure and the AI Service

Payoff information. Each informed investor i observes a private signal about the payoff,

$$s_i = v + \epsilon_i, \qquad \epsilon_i \sim \mathcal{N}(0, \tau_\epsilon^{-1}). \tag{4}$$

Retail investors have no information about the payoff.

The AI service. At date 0, each retail investor decides whether to use the AI service. Retail investor i pays a cost c_i, which is deducted from her terminal wealth if she adopts. Costs are drawn independently across retail investors from a distribution F_c and are independent of all shocks. A common cost c is the special case in which F_c is degenerate. Let $\lambda \in [0, 1]$ denote the fraction of retail investors who adopt, and let $\mathcal{A}$ be the set of adopters, which has mass $(1-\alpha)\lambda$. A mass $1-(1-\alpha)\lambda$ of investors, which includes all informed investors, does not use AI.

At date 1, before trading, the users of the service disclose their endowments to it in the course of their conversations. By the law of large numbers, the average endowment that users disclose reveals the aggregate endowment shock:

$$\frac{1}{(1-\alpha)\lambda} \int_{\mathcal{A}} u_j \, dj = \frac{1}{(1-\alpha)\lambda} \int_{\mathcal{A}} (u + \nu_j) \, dj = u \quad \text{a.s.}, \qquad \lambda > 0. \tag{5}$$

The idiosyncratic components average out, and the service learns u almost surely whenever a positive mass of investors uses it, however small. It returns to each user i the signal

$$r_i = u + \xi_i, \qquad \xi_i \sim \mathcal{N}(0, \tau_\xi^{-1}), \tag{6}$$

where the error ξ_i is specific to user i. It captures the noise with which the service's assessment

reaches an individual user, for example through the particular conversation in which it is delivered. The AI signal contains no information about the payoff v or about noise trading ω. Its value comes only from helping its users to interpret the price.

The precision τ_ξ does not depend on the adoption rate, so that the model has no data network effect. A precision that rose with adoption would create a complementarity in adoption mechanically. The complementarity derived in Section 6 arises instead from how the AI signal interacts with learning from the price.

Two features of the AI service are essential. First, the AI is valuable only because it aggregates private information. Public information about the payoff is summarized by the prior, and in a rational expectations equilibrium investors already know how the price depends on the shocks. An AI that processed only public data, past prices included, would add little to what an investor learns from the prior and the current price. Second, what the AI aggregates is information about supply. Its users are retail investors, who have no information about the payoff to disclose, but who know their own endowments.

Information sets. At date 1, every investor observes her own endowment and the price. Let $\mathcal{I}_i$ denote investor i's private information:

$$\mathcal{I}_i = \begin{cases} \{u_i\} & \text{if } i \text{ is a retail investor who does not use AI,} \\ \{r_i, u_i\} & \text{if } i \text{ is a retail investor who uses AI,} \\ \{s_i, u_i\} & \text{if } i \text{ is informed.} \end{cases} \tag{7}$$

Each investor conditions her trade on $\mathcal{I}_i$ and on the price p. Table 1 summarizes what each piece of information is good for. Only informed investors have direct information about the payoff. Every investor, however, has information about the aggregate endowment shock, which moves the price but is unrelated to the payoff.

Timing. The timing is as follows.

Date 0. Retail investors observe their costs and decide whether to adopt. The adoption rate λ becomes common knowledge.

Table 1: Information at date 1. Every investor also observes the price p. Nobody has information about noise trading ω.

Investor (mass)	Private information $\mathcal{I}_i$	Information about v	Information about u
Retail, no AI $((1-\alpha)(1-\lambda))$	u_i	none	u_i
AI user $((1-\alpha)\lambda)$	r_i, u_i	none	u_i and r_i
Informed (α)	s_i, u_i	s_i	u_i

Date 1. The shocks v, u, ω, and the idiosyncratic shocks are realized. Each investor observes her endowment u_i, and each informed investor observes her signal s_i. AI users disclose their endowments to the service and receive their signals r_i. Investors then submit demand schedules that are contingent on their private information, noise traders supply ω, and the market clears at price p.

Date 2. The risky asset pays v, adopters pay their costs, and investors consume.

Figure 1 summarizes the information structure.

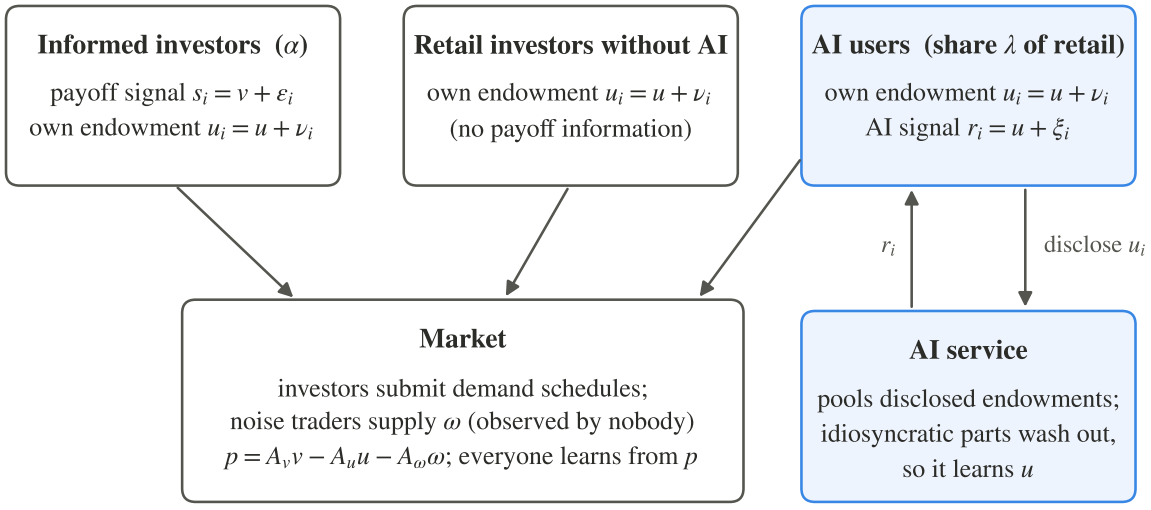


Figure 1: Information structure. Every investor knows her own endowment $u_i = u + \nu_i$. Informed investors also observe a signal about the payoff. The AI service pools the endowments disclosed by its users, learns the aggregate endowment shock u, and returns $r_i = u + \xi_i$ to each user. Investors submit demand schedules, noise traders supply ω, and every investor learns from the price.

3.4 Investors' Problems

Portfolio choice at date 1. Investor i takes the price as given and chooses her net purchase x_i to maximize

$$\mathbb{E}\left[-\exp(-\gamma W_i) \mid \mathcal{I}_i, p\right]. \tag{8}$$

Let

$$\mu_i \equiv \mathbb{E}[v \mid \mathcal{I}_i, p], \qquad \tau_i \equiv \mathrm{Var}(v \mid \mathcal{I}_i, p)^{-1} \tag{9}$$

denote her posterior mean and posterior precision of the payoff. I write τ_I, τ_A, and τ_U for the posterior precision of an informed investor, an AI user, and a retail investor without AI. Section 4 derives μ_i and τ_i for each type of investor.

Adoption at date 0. At date 0, a retail investor knows neither her endowment nor the price. She compares her ex-ante expected utility with and without AI, taking as given the adoption rate λ and the trading equilibrium at date 1. Because she is negligible, her own choice affects neither. Let W_i^A and W_i^U denote the terminal wealth (3), before the cost of AI, of a retail investor who uses AI and of one who does not, when each trades optimally at date 1. The investor adopts if

$$\mathbb{E}\left[-\exp\big(-\gamma(W_i^A - c_i)\big)\right] > \mathbb{E}\left[-\exp(-\gamma W_i^U)\right],$$

that is, if her cost is below the certainty-equivalent value of AI,

$$c_i < G_A(\lambda) \equiv \frac{1}{\gamma} \ln \frac{\mathbb{E}\left[\exp(-\gamma W_i^U)\right]}{\mathbb{E}\left[\exp(-\gamma W_i^A)\right]}, \tag{10}$$

and she does not adopt if $c_i > G_A(\lambda)$. A retail investor could alternatively acquire a payoff signal of precision τ_ϵ, which would make her an informed investor; I write $G_I(\lambda)$ for the analogous certainty-equivalent value of that signal. With CARA preferences and normal posteriors, both values are functions of posterior precisions alone (Appendix B.4):

$$G_A = \frac{1}{2\gamma} \ln \frac{\tau_A}{\tau_U}, \qquad G_I = \frac{1}{2\gamma} \ln \frac{\tau_I}{\tau_U} = \frac{1}{2\gamma} \ln\Big(1 + \frac{\tau_\epsilon}{\tau_U}\Big), \tag{11}$$

where τ_U, τ_A, and $\tau_I = \tau_U + \tau_\epsilon$ are the posterior precisions about the payoff of a retail investor without AI, of an AI user, and of an informed investor, characterized in Section 4. These values are the same for every realization of the price and of the investor's endowment, and other investors' choices affect either value only through the price. G_I is the value of information in Grossman and Stiglitz (1980).

Because the service learns u almost surely as soon as a positive mass of investors uses it, I define $G_A(0) \equiv \lim_{\lambda \downarrow 0} G_A(\lambda)$, the value of AI when a vanishing mass of retail investors uses it. When the trading equilibrium is continuous in λ, as under the conditions of Proposition 1(iv), $G_A(0)$ is the value of the signal (6) to a single investor in the market without AI.

3.5 Equilibrium Concept

I solve the model by backward induction. For a given adoption rate, the trading stage is a noisy rational expectations market. The equilibrium concept is standard (Vives, 2008, ch. 4).

Definition 1 (Rational expectations equilibrium for a given adoption rate)**.** Fix the adoption rate λ and the set of adopters $\mathcal{A}$. A rational expectations equilibrium consists of a price functional $P(v, u, \omega)$ and demand functions $X_U(u_i, p)$, $X_A(r_i, u_i, p)$, and $X_I(s_i, u_i, p)$ for retail investors without AI, AI users, and informed investors such that:

(i) *investors optimize*: given the price functional P, for every investor i and every realization of $(\mathcal{I}_i, p)$, her demand maximizes (8), where expectations are taken with respect to the joint distribution of $(v, \mathcal{I}_i, p)$ implied by $p = P(v, u, \omega)$;

(ii) *the market clears*: for almost every realization of the shocks,

$$\int_0^1 x_i \, di = \omega \quad \text{a.s.}, \qquad p = P(v, u, \omega), \tag{12}$$

where x_i is investor i's demand from (i) evaluated at her private information and the price.

In particular, every trader correctly understands the information conveyed by the equilibrium price.

Condition (i) is the rational expectations requirement: investors know how the price depends on the shocks and use it as a signal when they trade. The price functional depends on the shocks only through (v, u, ω) because idiosyncratic shocks average out in aggregate demand almost surely.

I restrict attention to linear equilibria, in which the price functional is linear in the shocks, as is standard. Because all shocks have mean zero, the intercept of a linear price functional is zero, so that

$$p = A_v v - A_u u - A_\omega \omega. \tag{13}$$

In a linear equilibrium all random variables are jointly normal, and posterior precisions are constants. I refer to a linear rational expectations equilibrium as a *trading equilibrium*.

An *adoption equilibrium* consists of an adoption rate λ^*, a set of adopters $\mathcal{A}^*$ of mass $(1-\alpha)\lambda^*$, and a trading equilibrium for λ^* such that every retail investor's adoption decision is optimal given the value of AI $G_A(\lambda^*)$ that this trading equilibrium implies: retail investors with $c_i < G_A(\lambda^*)$ adopt, and those with $c_i > G_A(\lambda^*)$ do not. I assume that the distribution of costs F_c is continuous; a common cost is the limiting case in which it is degenerate. By the law of large numbers, the fraction of retail investors with costs below $G_A(\lambda^*)$ is F_c evaluated at $G_A(\lambda^*)$, so an equilibrium adoption rate satisfies

$$\lambda^* = F_c\big(G_A(\lambda^*)\big). \tag{14}$$

With a common cost c, no adoption is an equilibrium if $G_A(0) \leq c$, full adoption is an equilibrium if $G_A(1) \geq c$, and an interior adoption rate $\lambda^* \in (0,1)$ is an equilibrium if $G_A(\lambda^*) = c$. When the trading stage has several equilibria for a given adoption rate (Section 4.8), the value of AI depends on which of them investors coordinate on, and an adoption equilibrium specifies this selection. Section 4 characterizes the trading equilibrium, and Section 6 studies the adoption decision.

4 Rational Expectations Equilibrium for a Fixed Adoption Rate

This section characterizes the trading equilibrium for a fixed adoption rate. The central theme is how investors use their supply information, and in particular the AI signal, to extract information about the payoff from the price. Appendix B.1 contains the proof of Proposition 1.

4.1 Optimal Demand

In a linear equilibrium, the payoff is normally distributed conditional on $(\mathcal{I}_i, p)$, with mean μ_i and precision τ_i as defined in (9). Terminal wealth (3) is then normal conditional on $(\mathcal{I}_i, p)$, and investor i's optimal net purchase is the standard CARA-normal demand,

$$x_i = \frac{\tau_i}{\gamma}(\mu_i - p) - u_i. \tag{15}$$

Market clearing (12) can therefore be written as $\frac{1}{\gamma}\int_0^1 \tau_i(\mu_i - p)\, di = u + \omega$ a.s. Because posterior precisions are constant within each type of investor, I index posterior precisions, posterior means, and demands by type: (τ_U, μ_U, x_U) for a retail investor without AI, (τ_A, μ_A, x_A) for an AI user, and (τ_I, μ_I, x_I) for an informed investor. Posterior means and demands depend on the investor's own signals, which keep the index i.

4.2 The Price as a Signal

Investors conjecture a linear price (13) with $A_v > 0$. Let $\beta_u \equiv \frac{A_v}{A_u}$ and $\beta_\omega \equiv \frac{A_v}{A_\omega}$. Dividing the price by A_v shows that observing the price is equivalent to observing a noisy signal of the payoff,

$$z_1 \equiv \frac{p}{A_v} = v + \zeta_p, \qquad \zeta_p \equiv -\beta_u^{-1} u - \beta_\omega^{-1}\omega, \qquad \tau_p \equiv \mathrm{Var}(\zeta_p)^{-1} = \left[\frac{\beta_u^{-2}}{\tau_u} + \frac{\beta_\omega^{-2}}{\tau_\omega}\right]^{-1}. \tag{16}$$

The price is thus a noisy signal of the payoff, and ζ_p is the price noise. The ratios β_u^{-1} and β_ω^{-1} are the price impacts of the endowment shock and of noise trading relative to the price

response to the payoff. The smaller they are, the more the price reveals about the payoff. The precision of the payoff conditional on the price alone is $\tau_v + \tau_p$. I refer to τ_p as *price informativeness*: the precision of the price as a signal of the payoff for an observer without supply information.

The price noise contains the aggregate endowment shock, and every investor has also private information about this shock (Table 1). Learning about u therefore removes part of the noise from the price. To derive her posterior, each investor transforms her information into signals of the payoff, $z_k = v + \zeta_k$, whose errors are mutually uncorrelated and independent of v. With normal shocks, such signals combine by adding precisions: with $\tau_k \equiv \text{Var}(\zeta_k)^{-1}$ and a prior mean of zero,

$$\tau_i = \tau_v + \sum_k \tau_k, \qquad \mu_i = \frac{\sum_k \tau_k z_k}{\tau_i}. \tag{17}$$

The three types of investors share the price signal z_1 and differ in the information that they bring to it.

4.3 Retail Investors without AI

A retail investor without AI learns from the price as in Hellwig (1980), with the addition of Manzano and Vives (2011) that her endowment is a private signal of the aggregate endowment shock, which is part of the noise in the price. A low price can reflect bad news about the payoff or a large endowment shock. An investor with a large endowment attributes more of a low price to the shock and infers a higher payoff from it than an investor with a small endowment. Investors therefore learn from the price privately: the same price conveys different information to different investors.

Posterior beliefs. An investor without AI observes $\{p, u_i\}$. Adding $\delta_u \equiv \frac{\tau_u \beta_u}{\tau_p}$ times her endowment to the price signal gives a second signal of the payoff,

$$z_{2i} \equiv z_1 + \delta_u u_i = v + \zeta_{2i}, \qquad \zeta_{2i} \equiv (\delta_u - \beta_u^{-1})u + \delta_u \nu_i - \beta_\omega^{-1}\omega, \qquad \tau_2 \equiv \text{Var}(\zeta_{2i})^{-1}. \tag{18}$$

The weight δ_u is chosen to make the two errors uncorrelated, $\mathrm{Cov}(\zeta_{2i}, \zeta_p) = \frac{1}{\tau_p} - \frac{\delta_u \beta_u^{-1}}{\tau_u} = 0$, and the two signals contain the same information as $\{p, u_i\}$. By (17), her posterior precision and mean are

$$\tau_U = \tau_v + \tau_p + \tau_2, \qquad \tau_p + \tau_2 = \left[\frac{\beta_u^{-2}}{\tau_u + \tau_\nu} + \frac{\beta_\omega^{-2}}{\tau_\omega} \right]^{-1}, \tag{19}$$

$$\mu_U = \frac{\tau_p z_1 + \tau_2 z_{2i}}{\tau_U} = \frac{\tau_p + \tau_2}{\tau_U} \left(z_1 + \beta_u^{-1} \frac{\tau_\nu}{\tau_u + \tau_\nu} u_i \right), \tag{20}$$

where the second expressions follow from substituting (16) and (18). The second expression for μ_U shows that the investor corrects the price signal for her forecast of its noise, $\mathbb{E}[\zeta_p \mid u_i] = -\beta_u^{-1} \frac{\tau_\nu}{\tau_u + \tau_\nu} u_i$, and treats the corrected price as a signal of the payoff with precision $\tau_p + \tau_2$. By (19), the noise that remains after the correction has two parts: the part of the endowment shock that her endowment does not explain, and noise trading, each times its squared relative price impact. Supply information reduces only the first part. Hence τ_p is what the price reveals to an outside observer, and τ_2 is what private learning adds.

How much private learning adds. The investor's endowment is valuable only through its correlation with the noise in the price. If it explains a share ρ^2 of the variance of the price noise, she interprets the price as a signal of the payoff with precision $\frac{\tau_p}{1-\rho^2}$, where τ_p is the precision of the price alone, so that private learning adds

$$\tau_2 = \frac{\rho^2}{1 - \rho^2} \tau_p, \qquad \rho^2 = \underbrace{\frac{\tau_\nu}{\tau_u + \tau_\nu}}_{\substack{\text{share of } u \text{ that her} \\ \text{endowment explains}}} \times \underbrace{\frac{\beta_u^{-2} \tau_u^{-1}}{\beta_u^{-2} \tau_u^{-1} + \beta_\omega^{-2} \tau_\omega^{-1}}}_{\substack{\text{share of the price} \\ \text{noise due to } u}}. \tag{21}$$

The share ρ^2 is the product of two shares. The first describes the investor: how well her endowment tracks the aggregate endowment shock. The second describes the market: how much of the price noise comes from the endowment shock, which investors can learn about, rather than from noise trading, which they cannot. What private learning adds is thus a multiple of τ_p, the information about the payoff that the price contains. A signal about the payoff, by contrast, adds a fixed precision to what the investor knows, whatever the price reveals (Section 4.5).

Demand. By (15), her demand is

$$x_U = \frac{1}{\gamma}\left(\tau_p z_1 + \tau_2 z_{2i} - \tau_U p\right) - u_i = \frac{1}{\gamma}\left(\frac{\tau_p + \tau_2}{A_v} - \tau_U\right) p + \left(\frac{\tau_2 \delta_u}{\gamma} - 1\right) u_i, \tag{22}$$

where, comparing the two expressions for μ_U in (20),

$$\tau_2 \delta_u = \beta_u^{-1} \frac{\tau_\nu}{\tau_u + \tau_\nu}\left(\tau_p + \tau_2\right). \tag{23}$$

The coefficient on her endowment has two parts. She sells her endowment one for one, and she buys $\frac{\tau_2 \delta_u}{\gamma}$ units per unit of her endowment, because a large endowment raises her expectation of the payoff at a given price. By (23), these purchases are the product of the relative price impact of the endowment shock, the share of the shock that her endowment reveals, and the intensity $\frac{\tau_p + \tau_2}{\gamma}$ with which she trades on the corrected price. The last term is the property of supply information that Manzano and Vives (2011) emphasize: an investor trades on supply information only through the price, so she trades on it more the more informative the price is. On a payoff signal, by contrast, she trades with intensity $\frac{\tau_\epsilon}{\gamma}$ whatever the informativeness of the price (Section 4.5).

4.4 AI Users

The AI signal is a second signal of the aggregate endowment shock. An AI user is therefore an investor of Section 4.3 with more precise supply information, and her problem is solved in the same way.

Posterior beliefs. An AI user observes $\{p, u_i, r_i\}$. Her endowment and her AI signal are conditionally independent signals of u, so all that matters for her beliefs is their precision-weighted average,

$$u_i^A \equiv \frac{\tau_\nu u_i + \tau_\xi r_i}{\tau_\nu + \tau_\xi} = u + \nu_i^A, \qquad \nu_i^A \equiv \frac{\tau_\nu \nu_i + \tau_\xi \xi_i}{\tau_\nu + \tau_\xi}, \tag{24}$$

a signal of u with precision $\tau_\nu + \tau_\xi$. Adding δ_u times this combined supply signal to the price signal gives a second signal of the payoff,

$$z_{2i}^A \equiv z_1 + \delta_u u_i^A = v + \zeta_{2i}^A, \qquad \zeta_{2i}^A \equiv (\delta_u - \beta_u^{-1})u + \delta_u \nu_i^A - \beta_\omega^{-1}\omega, \qquad \tau_2^A \equiv \mathrm{Var}(\zeta_{2i}^A)^{-1}, \quad (25)$$

with the same weight δ_u as in (18), because u_i^A and u_i have the same covariance with the price noise. Her posterior follows as in Section 4.3, with u_i^A in place of u_i and $\tau_\nu + \tau_\xi$ in place of τ_ν:

$$\tau_A = \tau_v + \tau_p + \tau_2^A, \qquad \tau_p + \tau_2^A = \left[\frac{\beta_u^{-2}}{\tau_u + \tau_\nu + \tau_\xi} + \frac{\beta_\omega^{-2}}{\tau_\omega}\right]^{-1}, \quad (26)$$

$$\mu_A = \frac{\tau_p z_1 + \tau_2^A z_{2i}^A}{\tau_A} = \frac{\tau_p + \tau_2^A}{\tau_A}\left(z_1 + \beta_u^{-1}\,\frac{\tau_\nu u_i + \tau_\xi r_i}{\tau_u + \tau_\nu + \tau_\xi}\right). \quad (27)$$

The AI user corrects the price for a more precise forecast of its noise: the part of the endowment shock that her supply information leaves unexplained has variance $\frac{1}{\tau_u+\tau_\nu+\tau_\xi}$ instead of $\frac{1}{\tau_u+\tau_\nu}$, and the part of the price noise due to noise trading is unchanged.

What the AI adds. The AI signal is a second signal of the endowment shock. In (21), it raises the first share, how well the investor's supply information tracks the shock, from $\frac{\tau_\nu}{\tau_u+\tau_\nu}$ to $\frac{\tau_\nu+\tau_\xi}{\tau_u+\tau_\nu+\tau_\xi}$, and leaves the second share, which is determined in equilibrium, unchanged. The AI therefore raises ρ^2, and the precision it adds to what the investor knows is again a multiple of τ_p: the AI multiplies the precision of price information rather than adding to it. Three properties of (19) and (26) are used throughout the paper.

First, the AI multiplies the precision of the investor's price information rather than adding to it:

$$\tau_p + \tau_2^A = (\tau_p + \tau_2)\,\Phi, \qquad \Phi \equiv \frac{\dfrac{\beta_u^{-2}}{\tau_u + \tau_\nu} + \dfrac{\beta_\omega^{-2}}{\tau_\omega}}{\dfrac{\beta_u^{-2}}{\tau_u + \tau_\nu + \tau_\xi} + \dfrac{\beta_\omega^{-2}}{\tau_\omega}}. \quad (28)$$

The factor Φ is the ratio of the variances of the price noise that the investor cannot predict without and with AI. It is at its maximum, $\frac{\tau_u+\tau_\nu+\tau_\xi}{\tau_u+\tau_\nu}$, when the endowment shock accounts for all of the price noise, and it is one when noise trading does. The AI corrects the price only for the endowment shock, so as the price becomes more informative and noise trading makes

up a larger share of the remaining noise, Φ falls. This fall is what limits the complementarity in adoption (Section 6). A payoff signal, by contrast, adds the fixed precision τ_ϵ whatever the price reveals.

Second, both precisions rise when β_u^{-1} falls: a price that is less exposed to the endowment shock is a more precise signal for every investor.

Third, both precisions are bounded by $\beta_\omega^2 \tau_\omega$, the precision of the price information of an investor who knows the endowment shock exactly. Such an investor observes $v - \beta_\omega^{-1}\omega$, the aggregate information of informed investors contaminated only by noise trading (Grossman, 1976; Hellwig, 1980). An AI user approaches this bound as the AI signal becomes perfectly precise.

Demand. By (15), her demand is

$$x_A = \frac{1}{\gamma}\left(\frac{\tau_p + \tau_2^A}{A_v} - \tau_A\right) p + \frac{\tau_\xi}{\tau_\nu + \tau_\xi}\frac{\tau_2^A \delta_u}{\gamma}\, r_i + \left(\frac{\tau_\nu}{\tau_\nu + \tau_\xi}\frac{\tau_2^A \delta_u}{\gamma} - 1\right) u_i, \tag{29}$$

where, comparing the two expressions for μ_A in (27),

$$\tau_2^A \delta_u = \beta_u^{-1}\frac{\tau_\nu + \tau_\xi}{\tau_u + \tau_\nu + \tau_\xi}\left(\tau_p + \tau_2^A\right). \tag{30}$$

She trades on her combined supply signal with intensity $\frac{\tau_2^A \delta_u}{\gamma}$. By (30) and (23), she trades more on supply information than an investor without AI, both because her supply information reveals a larger share of the endowment shock and because the corrected price is a more precise signal to her.

4.5 Informed Investors

An informed investor observes $\{p, u_i, s_i\}$. Her supply information is her endowment, as for a retail investor without AI, so she uses z_1 and z_{2i} from (18). Her payoff signal $s_i = v + \epsilon_i$ is already a signal of the required form, with precision τ_ϵ and an error that is independent of

all other shocks. By (17),

$$\tau_I = \tau_v + \tau_p + \tau_2 + \tau_\epsilon, \qquad \mu_I = \frac{\tau_p z_1 + \tau_2 z_{2i} + \tau_\epsilon s_i}{\tau_I}, \tag{31}$$

and by (15), her demand is

$$x_I = \frac{1}{\gamma}\left(\frac{\tau_p + \tau_2}{A_v} - \tau_I\right) p + \frac{\tau_\epsilon}{\gamma}\, s_i + \left(\frac{\tau_2 \delta_u}{\gamma} - 1\right) u_i. \tag{32}$$

An informed investor trades on her payoff signal with intensity $\frac{\tau_\epsilon}{\gamma}$, independently of how informative the price is. A more informative price raises her posterior precision τ_I but lowers the weight $\frac{\tau_\epsilon}{\tau_I}$ of her signal in her posterior mean, and the two effects cancel (Grossman and Stiglitz, 1980; Vives, 2008). Informed investors' aggregate demand therefore loads on the payoff with coefficient $\frac{\alpha\tau_\epsilon}{\gamma}$ at every adoption rate. Her trading on supply information is the same as that of a retail investor without AI. Table 2 summarizes the three investors' problems.

Table 2: Investors' problems at date 1.

	Retail investor without AI	AI user	Informed investor
Observes	p, u_i	p, u_i, r_i	p, u_i, s_i
Supply signal	u_i, precision τ_ν	u_i^A, precision $\tau_\nu + \tau_\xi$	u_i, precision τ_ν
Independent signals	z_1, z_{2i}	z_1, z_{2i}^A	z_1, z_{2i}, s_i
Posterior precision	$\tau_U = \tau_v + \tau_p + \tau_2$	$\tau_A = \tau_v + \tau_p + \tau_2^A$	$\tau_I = \tau_v + \tau_p + \tau_2 + \tau_\epsilon$
$\gamma\times$ coefficient on p	$\frac{\tau_p+\tau_2}{A_v} - \tau_U$	$\frac{\tau_p+\tau_2^A}{A_v} - \tau_A$	$\frac{\tau_p+\tau_2}{A_v} - \tau_I$
$\gamma\times$ coefficient on own signal	—	$\frac{\tau_\xi \tau_2^A \delta_u}{\tau_\nu+\tau_\xi}$ on r_i	τ_ϵ on s_i
$\gamma\times$ coefficient on u_i	$\tau_2\delta_u - \gamma$	$\frac{\tau_\nu \tau_2^A \delta_u}{\tau_\nu+\tau_\xi} - \gamma$	$\tau_2\delta_u - \gamma$

4.6 Characterization

Idiosyncratic shocks average out in aggregate demand almost surely: payoff signals aggregate to v, supply signals to u, and user-specific AI errors to nothing. Market clearing therefore gives a price that is linear in (v, u, ω), and matching coefficients characterizes the equilibrium.

Proposition 1 (Trading equilibrium)**.** *Fix the adoption rate* λ*.*

(i) In every trading equilibrium, $\beta_\omega = \frac{\alpha\tau_\epsilon}{\gamma}$, and β_u solves

$$\beta_u = f_\lambda(\beta_u) \equiv \frac{\alpha\tau_\epsilon}{\gamma} + \frac{\alpha^2\tau_\epsilon^2\tau_\omega\,\beta_u^2}{\gamma}\left[\frac{\big(1-(1-\alpha)\lambda\big)\tau_\nu}{\alpha^2\tau_\epsilon^2\tau_\omega + \gamma^2(\tau_u+\tau_\nu)\beta_u^2} + \frac{(1-\alpha)\lambda\,(\tau_\nu+\tau_\xi)}{\alpha^2\tau_\epsilon^2\tau_\omega + \gamma^2(\tau_u+\tau_\nu+\tau_\xi)\beta_u^2}\right]. \quad (33)$$

The function f_λ is increasing, with slope

$$f'_\lambda(\beta_u) = \frac{2\alpha^4\tau_\epsilon^4\tau_\omega^2\,\beta_u}{\gamma}\left[\frac{\big(1-(1-\alpha)\lambda\big)\tau_\nu}{\big(\alpha^2\tau_\epsilon^2\tau_\omega + \gamma^2(\tau_u+\tau_\nu)\beta_u^2\big)^2} + \frac{(1-\alpha)\lambda\,(\tau_\nu+\tau_\xi)}{\big(\alpha^2\tau_\epsilon^2\tau_\omega + \gamma^2(\tau_u+\tau_\nu+\tau_\xi)\beta_u^2\big)^2}\right] > 0. \quad (34)$$

(ii) The price coefficients are

$$A_v = \frac{\alpha\tau_\epsilon + \tau_p + \tau_2 + (1-\alpha)\lambda(\tau_2^A - \tau_2)}{\tau_v + \alpha\tau_\epsilon + \tau_p + \tau_2 + (1-\alpha)\lambda(\tau_2^A - \tau_2)}, \qquad A_u = A_v\beta_u^{-1}, \qquad A_\omega = \frac{\gamma}{\alpha\tau_\epsilon}\,A_v, \quad (35)$$

where $\tau_p + \tau_2$ and $\tau_p + \tau_2^A$ are given by (19) and (26) at $\beta_\omega = \frac{\alpha\tau_\epsilon}{\gamma}$.

(iii) A trading equilibrium exists, and in every equilibrium the endowment shock moves the price less than noise trading does, relative to fundamentals: $\beta_u^{-1} < \beta_\omega^{-1}$.

(iv) The equilibrium is unique under either of two conditions. The first bounds the slope of the best response at every conjecture:

$$\frac{27\alpha^2\tau_\epsilon^2\tau_\omega}{64\gamma^4}\left[\big(1-(1-\alpha)\lambda\big)\frac{\tau_\nu}{\sqrt{\tau_u+\tau_\nu}} + (1-\alpha)\lambda\,\frac{\tau_\nu+\tau_\xi}{\sqrt{\tau_u+\tau_\nu+\tau_\xi}}\right]^2 < 1, \quad (36)$$

in which case $f'_\lambda(\beta_u) < 1$ for every $\beta_u > 0$. The second is

$$8\gamma^2 \geq \alpha\tau_\epsilon\tau_\omega\left[\big(1-(1-\alpha)\lambda\big)\frac{\tau_\nu}{\tau_u+\tau_\nu} + (1-\alpha)\lambda\,\frac{\tau_\nu+\tau_\xi}{\tau_u+\tau_\nu+\tau_\xi}\right]. \quad (37)$$

Since the bracket in (37) is below one, (37) holds at every adoption rate and for every precision of the AI signal if

$$8\gamma^2 \geq \alpha\tau_\epsilon\tau_\omega. \quad (38)$$

Under (36) or the strict version of (37) the unique equilibrium is stable, $f'_\lambda(\beta_u) < 1$, and differentiable in adoption.

Proof. See Appendix B.1. □

Remark 1 (Relation to Manzano and Vives, 2011). Without AI and without noise trading, the model is the model of Manzano and Vives (2011) with uncorrelated errors in the payoff signals. With $\lambda = 0$ and $\tau_\omega \to \infty$, (33) becomes $\beta_u = \frac{\alpha\tau_\epsilon + \tau_\nu \beta_u^2}{\gamma}$, their fixed point for the ratio of price coefficients with a mass α of informed traders, idiosyncratic endowment precision τ_ν, and risk tolerance $\frac{1}{\gamma}$. In their model, correlation among signal errors bounds how precisely the price can be interpreted and guarantees existence; without it, a linear equilibrium exists only if $\gamma^2 \geq 4\alpha\tau_\epsilon\tau_\nu$. Here noise trading plays this role through the bound $\beta_\omega^2\tau_\omega$.

Intuition. The relative price impact of noise trading, $\frac{\gamma}{\alpha\tau_\epsilon}$, is the inverse of informed investors' aggregate trading intensity, as in Hellwig (1980): nobody can identify noise trading, so it is cleared through the price alone, and the more aggressively informed investors trade on their information, the less it moves the price relative to fundamentals. It does not depend on AI, because AI users have no information about the payoff. The endowment shock moves the price less (part (iii)), because investors have private information about it and trade against it, as in Manzano and Vives (2011). The function f_λ is their aggregate best response. It maps the relative price impact of the endowment shock that investors conjecture into the one that their trading produces. Its slope measures the strategic complementarity in the use of information that private learning creates; Section 4.7 explains why it is positive. An equilibrium is stable if the best response crosses the diagonal from above, $f'_\lambda < 1$. Noise trading bounds the complementarity, because nobody can interpret the price with a precision above $\beta_\omega^2\tau_\omega$, and this bound guarantees existence (part (iii)); in Manzano and Vives (2011), who have no noise trading, correlated errors in the payoff signals play this role (Remark 1).

4.7 Strategic Complementarity in Trading

Trading on supply information is a strategic complement: the more investors trade on their supply information, the more attractive it becomes for each of them to do so. The reason

is the private learning channel of Manzano and Vives (2011). Supply information is useful only for interpreting the price, so an investor trades on it in proportion to the weight she puts on the price. When more investors trade on their supply information, the endowment shock has a smaller price impact and the price is a more precise signal of the payoff; every investor then puts more weight on the price, and therefore trades more on her own supply information. The fixed point (33) is the best-response map of this complementarity: it maps the relative price impact of the endowment shock that investors conjecture into the one that their trading produces, and it is increasing.

The complementarity is the one that Ganguli and Yang (2009) and Manzano and Vives (2011) identify. In both papers it arises at the trading stage from the same source, investors' private information about supply, and it does not depend on what investors can acquire: a signal about the payoff in Manzano and Vives (2011), a bundle of payoff and supply signals in Ganguli and Yang (2009). At the trading stage the distribution of information is given, so their analysis applies here with two additions: noise trading, which bounds how precise a signal the price can be, and the AI signal, which gives some investors more precise supply information. What investors acquire matters only in Section 6, where the question is whether the complementarity in trading carries over to the acquisition of supply information.

A strategic complementarity of this kind can make price informativeness self-fulfilling. If investors expect the price to be informative, they put much weight on it and trade much on their supply information; the endowment shock then has a small price impact, and the price is indeed informative. If they expect the price to be uninformative, the reverse holds. Manzano and Vives (2011) show that with private learning from prices the trading stage generically has one or three regular equilibria, of which the extreme ones are stable and the middle one unstable; the same holds here without AI, where β_u^{-1} solves a cubic, whereas with AI there can be five (Appendix B.1). Proposition 1(iv) rules the multiplicity out by bounding the strength of the complementarity in two ways. Condition (36) is the uniqueness condition of Manzano and Vives (2011, Proposition 3): the slope of the best response is below one at every conjecture, so the complementarity is moderate everywhere. Their other sufficient condition, that the use of information be a strategic substitute, cannot hold here, because informed investors trade on their payoff signals with an intensity that does not depend on the price

(Section 4.5), the case of uncorrelated signal errors in their model. Condition (37) instead bounds how investors' purchases based on supply information respond to the price impact of the endowment shock. These purchases based on supply information are hump-shaped in the price impact of the endowment shock, rising with it at first, because there is more to correct, and falling once the shock dominates the price, because investors then rely little on the price; (37) requires that the part of a shock that is cleared through the price, which rises in proportion to the price impact, dominate this decline. Noise trading makes this possible, because it bounds how precise a signal the price can be, at $\beta_\omega^2 \tau_\omega$: the condition says that this bound is at most eight times the aggregate precision of informed investors' signals, scaled by the average share of the endowment shock that investors' supply information explains. That share is larger for AI users, so the condition becomes harder to satisfy as adoption spreads; since it is below one, (38) suffices at every adoption rate and for every precision of the AI signal.

Following Manzano and Vives (2011), I call a trading equilibrium *regular* if $f'_\lambda(\beta_u) \neq 1$, that is, if f_λ crosses the diagonal at β_u rather than being tangent to it. At a regular equilibrium the implicit function theorem applies, so the equilibrium moves continuously and differentiably with the adoption rate and the other parameters. Equilibria that are not regular occur only where two equilibria merge, as in panel (b) of Figure 2, and hence only at isolated parameter values. A regular equilibrium is locally stable under adaptive best-response dynamics if $|f'_\lambda(\beta_u)| < 1$; since $f'_\lambda > 0$ here, this is equivalent to $f'_\lambda < 1$. With three regular equilibria, the extreme ones are stable and the middle one is unstable. At a regular equilibrium, adoption moves the price ratio according to

$$\frac{d\beta_u}{d\lambda} = \frac{\partial f_\lambda / \partial \lambda}{1 - f'_\lambda(\beta_u)}. \tag{39}$$

The numerator is the direct effect of adoption at a given conjecture, and the denominator is the multiplier from the complementarity in trading: a more informative price leads every investor to trade more on her supply information, which makes the price more informative still. At a stable equilibrium the multiplier is positive, and adoption lowers the relative price impact of the endowment shock. At an unstable equilibrium it is negative, and the

equilibrium responds perversely, as in Manzano and Vives (2011). This sign is what matters for information acquisition in Section 6.

In Section 5 and from Section 6.4 to Section 6.5, I assume the strict version of (38). The trading stage then has a unique and stable equilibrium at every adoption rate, so that prices and the value of AI are functions of the adoption rate and all multiplicity arises in the market for AI. Proposition 4 does not need this assumption: it holds at every stable trading equilibrium, whether or not the equilibrium is unique.

4.8 AI and Multiplicity at the Trading Stage

Adoption shifts the map up at every conjecture, because an AI user buys more against the endowment shock than the non-user she replaces, but not by a constant amount. Write the bracket in (33) as $\big(1-(1-\alpha)\lambda\big)h(\tau_\nu)+(1-\alpha)\lambda\, h(\tau_\nu+\tau_\xi)$, where

$$h(z)=\frac{z}{\alpha^2\tau_\epsilon^2\tau_\omega+\gamma^2(\tau_u+z)\beta_u^2},\qquad h'(z)=\frac{\alpha^2\tau_\epsilon^2\tau_\omega+\gamma^2\tau_u\beta_u^2}{\left[\alpha^2\tau_\epsilon^2\tau_\omega+\gamma^2(\tau_u+z)\beta_u^2\right]^2}>0.$$

Hence $h(\tau_\nu+\tau_\xi)>h(\tau_\nu)$ and $\frac{\partial f_\lambda(\beta_u)}{\partial\lambda}>0$: at any conjecture, an AI user buys more on her supply information than the non-user she replaces, and the price that clears the market is more informative. The shift is hump-shaped in the conjecture. It is small when investors expect an uninformative price, because then nobody trades much on supply information, and small again when they expect a very informative one, because then even investors without AI interpret the price nearly as well as noise trading allows; it is largest at intermediate conjectures. Whether the shift adds or removes equilibria therefore depends on where f_λ is close to the diagonal. Figure 2 shows both cases for parameters that violate (38). In panel (a), f_λ without AI crosses the diagonal once, at a low β_u, and stays slightly below it at intermediate conjectures, where the shift is largest; adoption of an AI of moderate precision lifts it above the diagonal there, and two further equilibria appear, an unstable one and a stable, more informative one. In panel (b), f_λ without AI dips slightly below the diagonal at low conjectures, which produces an uninformative and an unstable equilibrium in addition to an informative one; adoption of a more precise AI lifts the dip above the diagonal, the two equilibria merge and disappear, and only the informative equilibrium remains. Proposition 2

shows that the second case always occurs when the AI is precise enough and enough investors use it.

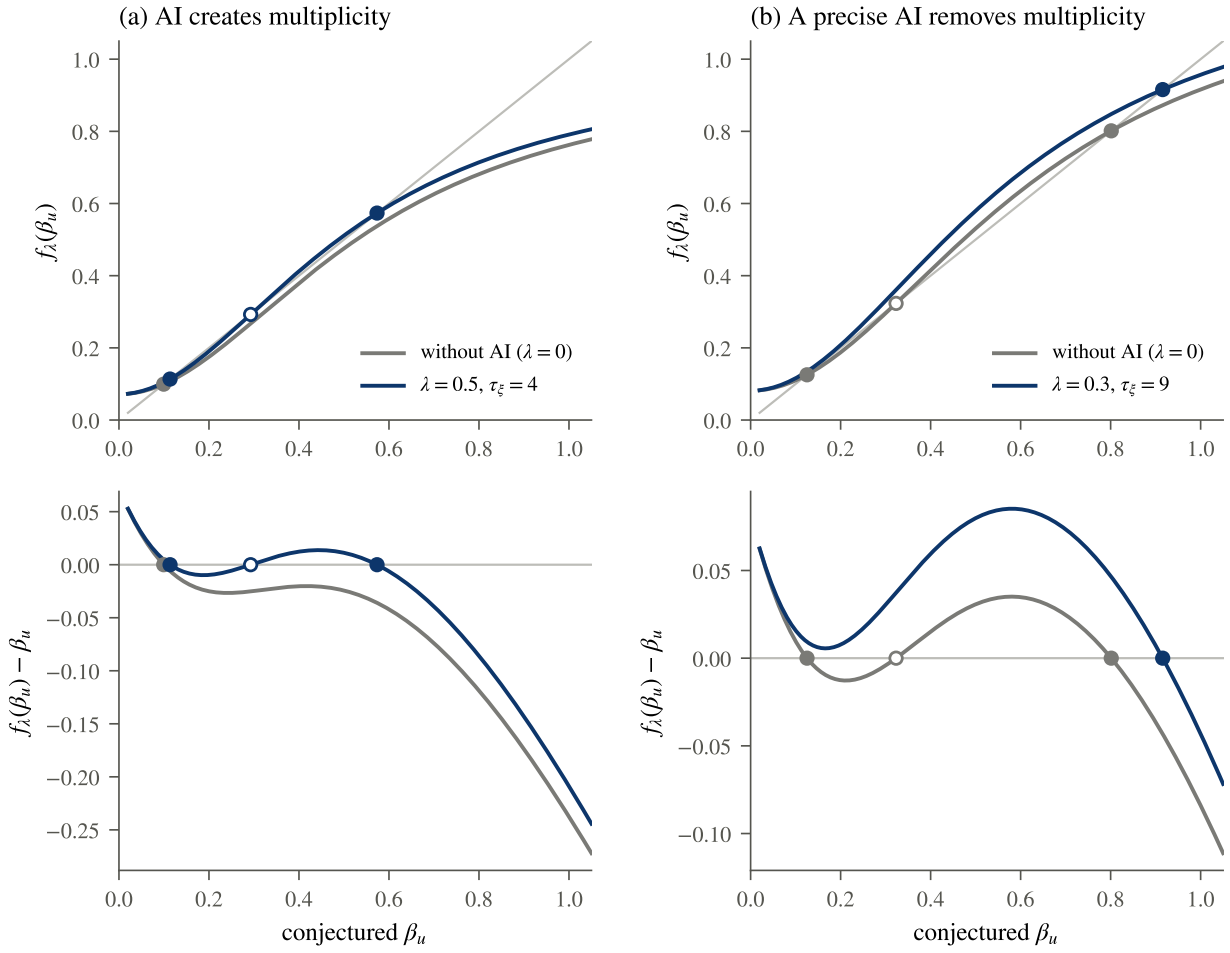


Figure 2: How AI shifts the aggregate best response. Top row: $f_\lambda(\beta_u)$ against the conjectured β_u and the 45-degree line; trading equilibria are the intersections. Bottom row: the excess $f_\lambda(\beta_u) - \beta_u$, whose zero crossings are the same equilibria; filled dots are stable equilibria and hollow dots unstable ones. Both panels: $\tau_v = \tau_\epsilon = \tau_u = 1$, $\tau_\nu = 9$, $\gamma = 3.08$, $\tau_\omega = 607.1$. Panel (a): $\alpha = 0.22$ and an AI of precision $\tau_\xi = 4$; a unique trading equilibrium without AI and three at an adoption rate of one half. Panel (b): $\alpha = 0.25$ and $\tau_\xi = 9$; three trading equilibria without AI and a unique one at an adoption rate of 0.3.

Proposition 2 (A precise AI eliminates multiplicity at the trading stage). *(i) Suppose that the AI signal reveals the endowment shock, $\tau_\xi = \infty$. Then the trading equilibrium is*

unique if the mass of AI users satisfies

$$(1-\alpha)\lambda \geq \frac{\dfrac{\tau_\nu}{\tau_u+\tau_\nu} - \dfrac{8\gamma^2}{\alpha\tau_\epsilon\tau_\omega}}{8+\dfrac{\tau_\nu}{\tau_u+\tau_\nu}}, \tag{40}$$

a threshold below $\frac{1}{9}$.

(ii) Suppose that $\tau_\xi \geq 3\tau_\omega - \tau_u - \tau_\nu$. *Then the trading equilibrium is unique if*

$$(1-\alpha)\lambda > \frac{1}{4} - \frac{2\gamma^2(\tau_u+\tau_\nu)}{\alpha\tau_\epsilon\tau_\omega\tau_\nu}, \tag{41}$$

a threshold below $\frac{1}{4}$.

Proof. See Appendix B.2. □

Both thresholds are positive only if (37) fails without AI, and both conditions are sufficient, not necessary: in panel (b) of Figure 2, the equilibrium is unique at a precision of the AI signal far below the cutoff in part (ii). Part (i) is the counterpart of Corollary 9 in Manzano and Vives (2011), the case in which informed traders observe the same signal and trade on it with a weight that does not depend on what the price reveals, as AI users do here on their supply information when the AI reveals the endowment shock. Their condition, $\Psi - \mu(\Psi+8) \leq 0$, with Ψ the share of the endowment shock that an endowment explains and μ the mass of informed traders, is (40) without the term in noise trading.

The uninformative equilibrium is self-fulfilling because investors who expect an imprecise price trade little on their supply information, so the endowment shock moves the price a lot and the price is indeed imprecise. A user of a precise AI does not behave this way. Under the condition on τ_ξ in part (ii), she knows the endowment shock well enough that her price information has at least three quarters of the maximal precision $\beta_\omega^2\tau_\omega$ at every conjecture, so her purchases against the shock vary little with what she expects; when the AI reveals the shock, they do not depend on it at all, just as informed investors' trading on their payoff signals does not depend on what others are expected to do. Once enough investors trade this way, aggregate demand responds strongly to the endowment shock at every conjecture, and the uninformative equilibrium disappears.

Proposition 2 has a direct reading in terms of the technology. The precision of the AI signal is what improves when the service improves: when users link their brokerage accounts so that the assistant observes their positions rather than descriptions of them (Section 2), when more of a user's trading needs are disclosed, and when the models themselves improve. Such improvements remove the self-fulfilling uninformative equilibrium at the trading stage once the share of retail investors who use the service exceeds the thresholds in Proposition 2, which are below one quarter and smaller when the variance of noise trading is large relative to informed trading. A better AI therefore makes the asset market less prone to multiplicity, not more. Conversely, a restriction on the data that the service may use, which lowers the precision of its signal, can move an economy back into the region in which the trading stage has several equilibria.

The source of multiple trading equilibria is thus private supply information, which every investor has, and AI changes the strength of the force that produces them. When the variance of noise trading is large enough for (38) to hold, the trading stage has a unique equilibrium at every adoption rate and for every AI technology, and the multiplicity in adoption of Section 6, which AI creates, arises at this unique and stable trading equilibrium. The complementarity in adoption that produces it does not itself depend on uniqueness: by Proposition 4(ii), when the trading stage has several equilibria, adoption is a complement at each stable one and a substitute at the unstable one.

5 Price Informativeness and Price Impact

This section compares the same economy at adoption rate λ and at $\lambda = 0$. Throughout, $8\gamma^2 > \alpha\tau_\epsilon\tau_\omega$, so the trading equilibrium is unique and differentiable in λ. I follow the organizing principle of Goldstein, Huang, and Yang (2025), who define fragility as the amplification of shocks and distinguish it from both price volatility and price informativeness. The model lends itself to this distinction, because the price

$$p = A_v(\lambda)\left[v - \beta_u(\lambda)^{-1}u - \frac{\gamma}{\alpha\tau_\epsilon}\,\omega\right] \tag{42}$$

separates into a *scale*, the response A_v to fundamentals, and a *composition*, the exposure to each nonfundamental shock per unit of exposure to fundamentals. Informativeness, τ_p, depends on the composition alone. Amplification, the loadings A_v, $A_u = A_v\beta_u^{-1}$, and $A_\omega = \frac{\gamma}{\alpha\tau_\epsilon}A_v$, depends on both. AI changes the scale and one element of the composition, the relative price impact of the endowment shock. The relative price impact of noise trading is the same with and without AI, because nobody learns about noise trading and informed investors trade on their signals with the same intensity.

5.1 Price Loadings

By (35), the price response to fundamentals A_v rises with the precision of investors' information. Adoption raises it through two channels. The *composition effect*: a mass of investors interprets the price with τ_2^A instead of τ_2. The *informativeness effect*: every investor, with or without AI, interprets a price that is less exposed to the endowment shock.

Proposition 3 (Adoption, price informativeness, and price impact)**.** *Consider a stable trading equilibrium, $f'_\lambda(\beta_u) < 1$; under $8\gamma^2 > \alpha\tau_\epsilon\tau_\omega$ this is the unique equilibrium at every adoption rate.*

(i) Adoption lowers the price impact of the endowment shock relative to fundamentals, $\frac{d\beta_u^{-1}}{d\lambda} < 0$, and raises price informativeness τ_p. At an unstable trading equilibrium, $f'_\lambda(\beta_u) > 1$, both signs are reversed.

(ii) Adoption raises the price response to fundamentals, $\frac{dA_v}{d\lambda} > 0$, which nevertheless stays below one.

(iii) Adoption raises the price impact of noise trading in the same proportion as the response to fundamentals: $\frac{A_\omega}{A_v} = \frac{\gamma}{\alpha\tau_\epsilon}$ does not depend on λ.

(iv) Price informativeness also rises with the mass of informed investors, for a given mass of AI users, and with risk tolerance $\frac{1}{\gamma}$.

Proof. See Appendix B.3. □

Intuition. In Grossman and Stiglitz (1980) and Hellwig (1980), the price becomes more informative when more investors trade on information about the payoff; the price then re-

sponds more to fundamentals, and noise trading moves it less relative to fundamentals, because informed investors trade against it more aggressively. Adoption makes the price more informative through a different channel. AI users bring no information about the payoff into the price; they trade against the endowment shock. Three things follow.

The endowment shock moves the price less relative to fundamentals, and the price becomes more informative (part (i)). This is the comparative static of Section 4.7: adoption shifts the best-response map up, because AI users trade more against the shock than the non-users they replace, and at the unique, stable equilibrium the complementarity in trading amplifies the shift.

The price responds more to fundamentals (part (ii)). The price is a precision-weighted average of investors' expectations of the payoff minus a risk premium proportional to supply, and expectations move with the payoff by more the better informed investors are. Adoption makes AI users better informed directly and all investors better informed through the price. Because expectations also put weight on the prior, the response stays below one: AI does not make the price overreact to news. No investor trades more because she expects others to do so; the price moves more with the payoff because investors know more about it.

Noise trading moves the price more (part (iii)). Nobody has information about noise trading, so the market cannot tell a noise-trader sale from a sale on bad news and reacts to both alike; as the price responds more to news, it responds more to noise trading in the same proportion. This is where adoption differs from informed trading, and the difference is the basis of the empirical test in Section 7: more informed trading lowers the relative price impact of noise trading, whereas adoption leaves it unchanged and raises its absolute price impact together with A_v. The composition of nonfundamental volatility changes accordingly. The share of noise trading in the price variance generated by the two supply shocks, $\frac{\tau_p}{\beta_\omega^2 \tau_\omega}$, rises with adoption: a market with AI reveals fundamentals better, and the noise that remains in its price comes increasingly from flows that no investor can learn about. The absolute price impact of the endowment shock, $A_u = A_v \beta_u^{-1}$, combines the fall in β_u^{-1} with the rise in A_v, and the proposition does not sign it.

Part (iv) and the reversal in part (i) are Proposition 4 of Manzano and Vives (2011). More informed trading and more risk tolerance shift the best-response map up, as adoption

does, and the multiplier of the complementarity in trading amplifies the shift at a stable equilibrium and reverses it at an unstable one.

Figure 3 illustrates Proposition 3 for two sets of parameters that satisfy the maintained condition. The solid lines are the equilibrium coefficients at each adoption rate and the dashed lines their values without AI. The dotted lines isolate the two channels. In the left panels, the dotted line is A_v computed at adoption rate λ but with the relative price impact of the endowment shock held at its value without AI, $\beta_u(0)^{-1}$: it shows how much of the rise in A_v is due to the change in the composition of investors alone, with the price no more informative than before, and the remainder is due to the price becoming more informative. In the middle panels, the dotted line is $A_v(\lambda)\beta_u(0)^{-1}$, the price impact of the endowment shock if only the scale A_v had changed and the relative price impact had stayed at its value without AI; the gap between it and the solid line is the fall in β_u^{-1} produced by AI users' purchases based on supply information. The informativeness effect is the part of what AI does to the price that works through the price itself: all investors, including those without AI, learn from a price that is less exposed to the endowment shock because AI users' demand responds more strongly to it.

Pricing error. Price informativeness, τ_p, is the precision with which the price forecasts the payoff. It is distinct from price efficiency in the sense of how far the price is from the payoff: $\mathrm{Var}(v-p) = \frac{(1-A_v)^2}{\tau_v} + \frac{A_v^2}{\tau_p}$, underreaction to the payoff plus nonfundamental variance, which I call the pricing error. The loading on the payoff that minimizes it is the Bayesian weight $\frac{\tau_p}{\tau_v+\tau_p}$, and the equilibrium loading exceeds it, because the price is set by investors who know more than the price alone. Adoption raises τ_p, which lowers the pricing error, and raises A_v, which raises it. The pricing error falls if and only if informativeness grows fast enough relative to the market's average precision (Appendix B.3). [TO BE COMPLETED]

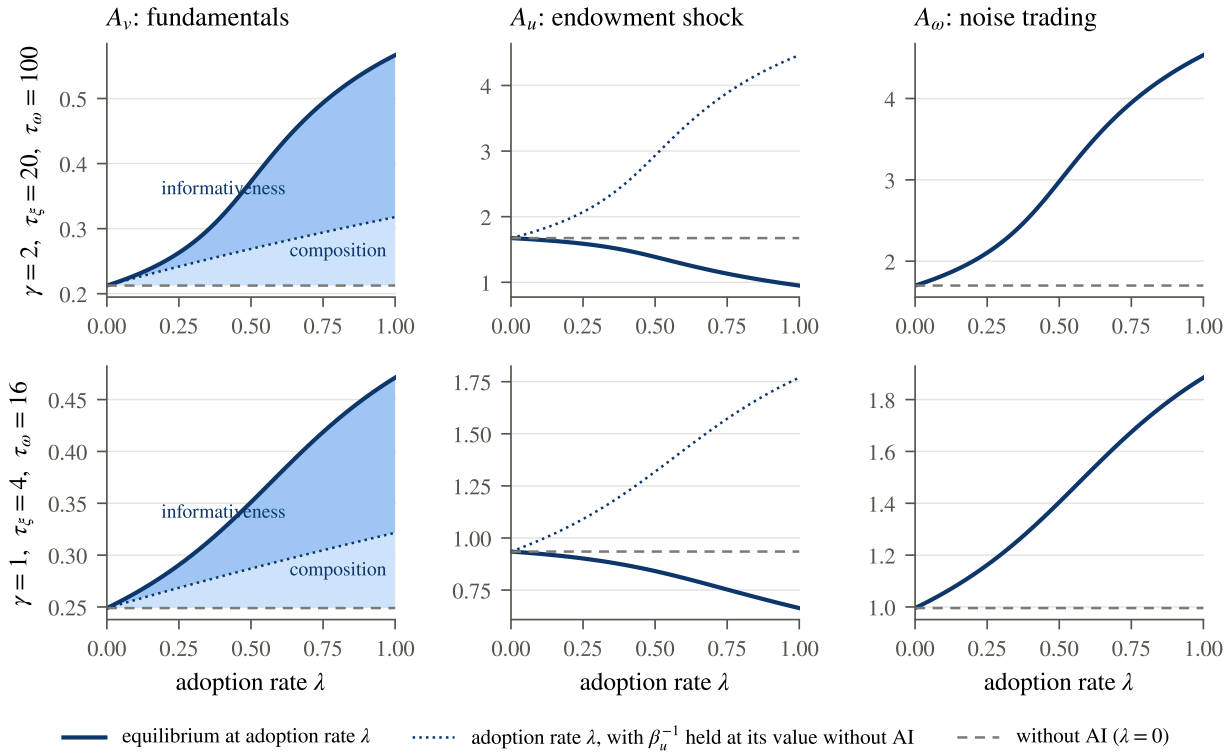


Figure 3: Price coefficients with and without AI. Solid lines: equilibrium coefficients at adoption rate λ. Dashed lines: their values without AI. Left panels: the dotted line is A_v at adoption rate λ with the relative price impact of the endowment shock held at its value without AI; the light area is the composition effect and the dark area the informativeness effect. Middle panels: the dotted line is $A_v(\lambda)\beta_u(0)^{-1}$, the price impact of the endowment shock if only the scale had changed. Parameters: $\alpha = 0.25$, $\tau_v = \tau_\epsilon = \tau_u = 1$, $\tau_\nu = 0.25$; top row $\gamma = 2$, $\tau_\xi = 20$, $\tau_\omega = 100$; bottom row $\gamma = 1$, $\tau_\xi = 4$, $\tau_\omega = 16$.

6 Information-Acquisition Incentives and Adoption Equilibria

This section turns from trading to information acquisition. It shows that the value of the AI signal can rise with the number of investors who use it, explains why information about the payoff cannot have this property at a stable trading equilibrium, and shows that the complementarity can make adoption self-fulfilling even when the asset market has a unique and stable equilibrium. The section proceeds in two steps. Sections 6.1 to 6.3 treat the adoption rate as a parameter, as Manzano and Vives (2011) treat the mass of informed traders, and ask how the value of AI, gross of its cost, changes with it at a given trading equilibrium; this is the standard definition of strategic complementarity in information acquisition, and it does not require the trading equilibrium to be unique. Sections 6.4 and 6.5 close the adoption stage as in Section 3.5; there the value of AI must be a function of the adoption rate, and I assume $8\gamma^2 > \alpha\tau_\epsilon\tau_\omega$.

6.1 Two Links: Why Payoff Information Is a Substitute

By (11), the value of a signal depends only on the investor's posterior precision with and without it, and other investors affect these precisions only through the price. This is the setting of the argument of Grossman and Stiglitz (1980) that information acquisition is a strategic substitute. When more investors acquire information, the price becomes more informative, which raises what an investor knows without her signal. A payoff signal adds the fixed precision τ_ϵ to this, so the ratio $\frac{\tau_I}{\tau_U} = 1 + \frac{\tau_\epsilon}{\tau_U}$ falls, and the signal is worth less. The argument has two links:

$$\frac{d\,(\text{value of a signal})}{d\,(\text{others' acquisition})} = \underbrace{\frac{\partial\,(\text{value of a signal})}{\partial\,(\text{price informativeness})}}_{\text{first link: depends on the signal}} \times \underbrace{\frac{d\,(\text{price informativeness})}{d\,(\text{others' acquisition})}}_{\text{second link: positive at stable equilibria}} . \quad (43)$$

The second link does not depend on the kind of information. It is positive at every stable trading equilibrium, because more information in the market shifts the best-response map up and the multiplier $\frac{1}{1-f'_\lambda}$ is positive (Proposition 3(i) for adoption), and negative only at an

unstable equilibrium, where the equilibrium responds perversely (Manzano and Vives, 2011). The first link depends on what the signal adds. A payoff signal adds a fixed precision, so the link is negative. The AI signal is information about the noise in the price, so it is useful only through the price, and what it adds is a multiple of the precision of price information, by (28), so that

$$G_A = \frac{1}{2\gamma} \ln \frac{\tau_v + (\tau_p + \tau_2)\,\Phi}{\tau_v + \tau_p + \tau_2}. \tag{44}$$

What the AI adds to its user's precision is $\tau_2^A - \tau_2 = (\tau_p + \tau_2)(\Phi - 1)$: the precision of a non-user's price information, times the proportional improvement $\Phi - 1$ that the AI brings to it. A payoff signal adds the constant τ_ϵ instead. This is where the two signals part. Holding Φ fixed, a more informative price raises the ratio of posterior precisions for the AI signal and lowers it for the payoff signal,

$$\begin{aligned}
\frac{\partial}{\partial(\tau_p + \tau_2)} \frac{\tau_v + (\tau_p + \tau_2)\Phi}{\tau_v + \tau_p + \tau_2} &= \frac{(\Phi - 1)\tau_v}{(\tau_v + \tau_p + \tau_2)^2} > 0, \\
\frac{\partial}{\partial(\tau_p + \tau_2)} \frac{\tau_v + \tau_p + \tau_2 + \tau_\epsilon}{\tau_v + \tau_p + \tau_2} &= -\frac{\tau_\epsilon}{(\tau_v + \tau_p + \tau_2)^2} < 0 :
\end{aligned}$$

a proportional improvement is worth more on a more precise base, a fixed one less. Against this, Φ itself falls as the price becomes more informative, because the AI removes only the endowment shock from the price noise and noise trading makes up a growing share of what remains. The first link is positive when the first effect dominates. Proposition 4 gives the exact condition.

6.2 Strategic Complementarity in Adoption

Proposition 4 (Strategic complementarity and substitutability in information acquisition)**.** *Treat the adoption rate λ as a parameter, and let $C \equiv \beta_\omega^2 \tau_\omega = \frac{\alpha^2 \tau_\epsilon^2 \tau_\omega}{\gamma^2}$ denote the maximal precision of price information, so that $\tau_v + C$ is the posterior precision of an investor who knows the endowment shock exactly, and define the threshold*

$$b^* \equiv \frac{\left[(\tau_u + \tau_\nu)(\tau_u + \tau_\nu + \tau_\xi)\right]^{1/4} \left(1 + \frac{C}{\tau_v}\right)^{1/4}}{\sqrt{C}}, \tag{45}$$

which depends only on the parameters of the model.

(i) Consider a stable trading equilibrium, $f'_\lambda(\beta_u) < 1$. Adoption is a strategic complement, $\frac{dG_A}{d\lambda} > 0$, when the price impact of the endowment shock relative to fundamentals exceeds the threshold,

$$\beta_u^{-1} > b^*, \tag{46}$$

and a strategic substitute when $\beta_u^{-1} < b^*$. In terms of posterior precisions, (46) is the same as

$$\tau_A \, \tau_U < \tau_v \, (\tau_v + C) : \tag{47}$$

the product of the posterior precisions of an AI user and of a retail investor without AI is below the product of the prior precision and the maximal posterior precision. At an unstable trading equilibrium the two signs are reversed.

(ii) Every trading equilibrium, at every adoption rate, satisfies

$$\beta_u < \bar{\beta} \equiv \frac{\alpha\tau_\epsilon}{\gamma}\Big(1 + \frac{\alpha\tau_\epsilon\tau_\omega}{\gamma^2}\Big) \tag{48}$$

and, writing

$$\chi_\lambda \equiv \frac{\alpha\tau_\epsilon\sqrt{\tau_\omega}}{\gamma^2}\left[\big(1-(1-\alpha)\lambda\big)\frac{\tau_\nu}{\sqrt{\tau_u+\tau_\nu}} + (1-\alpha)\lambda\,\frac{\tau_\nu+\tau_\xi}{\sqrt{\tau_u+\tau_\nu+\tau_\xi}}\right] \tag{49}$$

for the quantity that (36) bounds by $\frac{8}{3\sqrt{3}}$, also $\beta_u \leq \frac{\alpha\tau_\epsilon}{\gamma}\big(1-\frac{\chi_\lambda}{2}\big)^{-1}$ whenever $\chi_\lambda < 2$, in particular under (36). Hence, if

$$\frac{\tau_\omega}{\sqrt{(\tau_u+\tau_\nu)(\tau_u+\tau_\nu+\tau_\xi)}} \;>\; \Big(1+\frac{\alpha\tau_\epsilon\tau_\omega}{\gamma^2}\Big)^2\sqrt{1+\frac{\alpha^2\tau_\epsilon^2\tau_\omega}{\gamma^2\tau_v}}, \tag{50}$$

or if $\chi_1 < 2$ and (50) holds with $\big(1-\frac{\chi_1}{2}\big)^{-2}$ in place of $\big(1+\frac{\alpha\tau_\epsilon\tau_\omega}{\gamma^2}\big)^2$, then (46) holds at every trading equilibrium at every adoption rate: adoption is a strategic complement at every stable trading equilibrium and a strategic substitute at every unstable one. The set of parameters satisfying (50) is nonempty and open, and it intersects the uniqueness region $8\gamma^2 > \alpha\tau_\epsilon\tau_\omega$: for any α, τ_ϵ, τ_v, τ_u, τ_ν, τ_ξ, and any $\kappa > 0$, (50) holds for all τ_ω

above $(1+\kappa)^2\sqrt{(\tau_u+\tau_\nu)(\tau_u+\tau_\nu+\tau_\xi)}\sqrt{1+\frac{\alpha\tau_\epsilon\kappa}{\tau_v}}$ *when* γ *is set so that* $\frac{\alpha\tau_\epsilon\tau_\omega}{\gamma^2}=\kappa$.

(iii) At a stable trading equilibrium, acquiring the payoff signal is a strategic substitute: its value falls with the adoption rate and, for a given mass of AI users, with the mass of informed investors.

(iv) At a stable trading equilibrium, whenever adoption is a strategic complement, a larger mass of informed investors raises the value of the AI signal, for a given mass of AI users.

Under $8\gamma^2>\alpha\tau_\epsilon\tau_\omega$*, the trading equilibrium is unique and stable at every adoption rate, and the statements hold at that equilibrium.*

Proof. See Appendix B.5. □

Intuition. Part (i) is the central result: for the AI signal, the first link in (43) can be positive, so adoption can be a complement at a stable trading equilibrium, where payoff information is a substitute. Whether it is depends on how close the price is to the bound C that noise trading sets on its precision. Far from the bound, the endowment shock accounts for most of the price noise, for AI users and non-users alike; the AI then improves the interpretation of the price by nearly the same factor whatever the price reveals, and a more informative price makes this improvement worth more. Close to the bound, most of the noise that an AI user still faces is noise trading, which she cannot remove; further adoption then improves the price information of non-users more than hers, and the value of AI falls. Condition (47) is the exact dividing line: the product of the posterior precisions of an AI user and of a non-user must lie below the product of the prior precision and the maximal posterior precision τ_v+C. Condition (46) states the same line in terms of the price, as a threshold b^* on the relative price impact of the endowment shock that depends only on primitives. Since adoption lowers β_u^{-1} along a stable branch (Proposition 3(i)) while b^* does not move, the value of AI is single-peaked in adoption: it rises as long as $\beta_u^{-1}>b^*$ and falls thereafter.

Part (ii) turns the condition on the equilibrium into a condition on primitives. Whatever investors expect, their trading on supply information lowers the relative price impact of the endowment shock below that of noise trading by at most the factor $1+\frac{\alpha\tau_\epsilon\tau_\omega}{\gamma^2}$, its value if every

investor knew the shock exactly; this is (48). If the endowment shock still dominates the price noise at this bound, by the margin that (47) requires, then adoption is a complement at every stable equilibrium. Condition (50) says this in terms of primitives: the variance of the endowment shock that remains given investors' supply information must be large relative to the variance of noise trading. The condition is coarse, because it must hold at an extreme that no equilibrium reaches. The second bound in part (ii) uses instead that investors' purchases based on supply information are at most the peak of the hump of Section 4.7, the same object that the uniqueness conditions of Proposition 1(iv) bound; it is tighter than (48) when the variance of noise trading is small relative to the residual variance of the endowment shock, which is where (50) can hold. Appendix B.5 gives a further condition for the least informative equilibrium. Its value is to show that the complementarity holds on an open set of economies and does not depend on uniqueness of the trading equilibrium: with several, adoption is a complement at each stable one and a substitute at the unstable one, the reverse of the pattern for payoff information in Manzano and Vives (2011). Uniqueness is needed only from Section 6.4 on, to keep the multiplicity in the market for AI.

Parts (iii) and (iv) are the cross effects between the two kinds of information. Adoption makes the price more informative and, by the Grossman–Stiglitz argument, lowers the value of a payoff signal: adoption crowds out informed trading. A larger mass of informed investors raises the value of AI in two ways. It raises the bound C, because the price then contains more information about the payoff for the AI to uncover, which always raises the value of AI; and it makes the price more informative at a given bound, which raises the value of AI when (47) holds.

Figure 4 illustrates Proposition 4. The value of AI rises with adoption as long as (47) holds, peaks where it holds with equality, and falls thereafter; the value of the payoff signal falls throughout. The shaded regions mark the simpler sufficient condition that the AI user alone be below the geometric-mean bound, $\tau_A \leq \sqrt{\tau_v(\tau_v + C)}$, which implies (47).

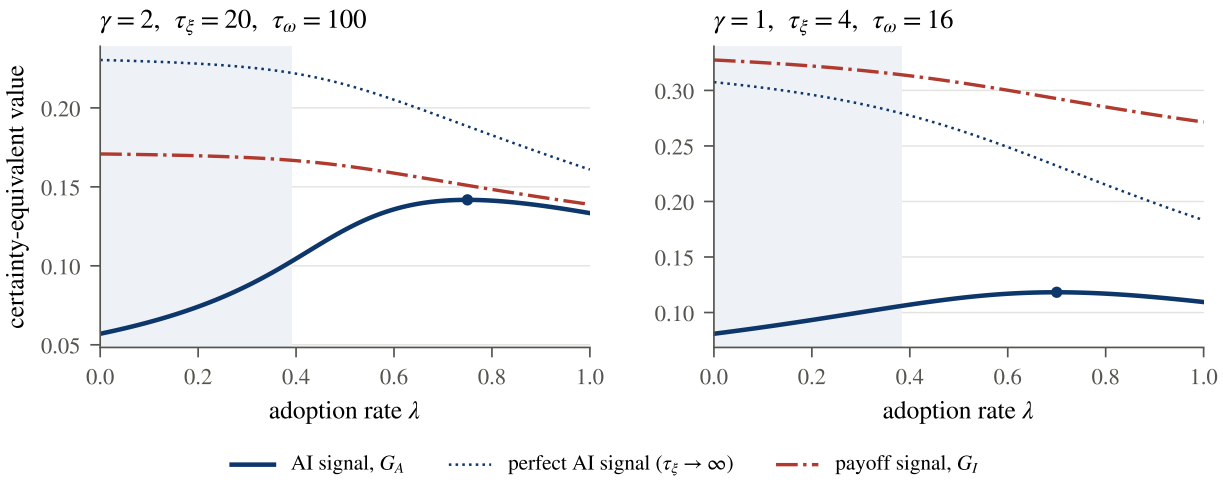


Figure 4: Values of information along the adoption path. Solid: the value of the AI signal, G_A; dotted: the value of a perfectly precise AI signal to a single investor, given the equilibrium of the economy; dash-dotted: the value of the payoff signal, G_I. Shaded: adoption rates at which the sufficient condition $\tau_A \leq \sqrt{\tau_v(\tau_v + C)}$ holds. The dot marks the maximum of G_A, at which (47) holds with equality. Parameters: $\alpha = 0.25$, $\tau_v = \tau_\epsilon = \tau_u = 1$, $\tau_\nu = 0.25$; left panel $\gamma = 2$, $\tau_\xi = 20$, $\tau_\omega = 100$; right panel $\gamma = 1$, $\tau_\xi = 4$, $\tau_\omega = 16$.

6.3 Why Payoff Information Cannot Generate the Complementarity

By Section 6.1, payoff information can be a complement only where others' acquisition makes the price less informative, that is, only at an unstable trading equilibrium. This is Manzano and Vives (2011, Proposition 6) for a market in which investors learn privately from the price through their endowments, as here, and it holds in the economy without AI as well.

Proposition 5 (Payoff information without AI)**.** *Without AI:*

(i) At every stable trading equilibrium, the value of the payoff signal falls with the mass of informed investors: acquiring payoff information is a strategic substitute. At an unstable trading equilibrium, a larger mass of informed investors raises the relative price impact of the endowment shock, which raises the value of the payoff signal, so that payoff information can be a strategic complement there.

(ii) If $8\gamma^2 > \frac{\tau_\epsilon \tau_\omega \tau_\nu}{\tau_u + \tau_\nu}$, the trading equilibrium is unique and stable for every mass of informed investors, and for every distribution of acquisition costs there is a unique equilibrium in the acquisition of payoff information.

Proof. See Appendix B.6. □

Part (i) is Proposition 6 of Manzano and Vives (2011): the signal acquired is the same, a payoff signal, and so is the mechanism. In both models, the mass of informed investors affects the value of the payoff signal only through the price, and a larger mass makes the price more informative at a stable trading equilibrium and less informative at an unstable one, so that the payoff signal is a substitute at the former and can be a complement only at the latter. Because the signal is the same, the only difference between the two results is noise trading, and it concerns the unstable case alone. In their model the sign is exactly reversed there. Here, informed trading also lowers the relative price impact of noise trading, which makes the price more informative at every equilibrium and lowers the value of the payoff signal; at an unstable equilibrium this works against the effect through the endowment shock, and the sign of the total effect is not determined. Panel (c) of Figure 5 illustrates part (i) for parameters at which the trading stage without AI has three equilibria for a range of masses of informed investors (Section 4.8): the value of the payoff signal rises with α only along the middle, unstable branch.

What separates the AI signal from the payoff signal is the signal itself, not the equilibrium at which it is acquired: the AI signal can reverse the sign of the first link. In Manzano and Vives (2011), private learning from the price strengthens the complementarity in the *use* of information, but it is not an object of acquisition: each investor receives her endowment for free, and what she can buy is payoff information. With AI, the private-learning channel itself becomes the object of acquisition. The proof of Proposition 4 follows theirs and differs in one place, the sign of $\frac{\partial G_A}{\partial \beta_u}$, which is always negative for a payoff signal and positive under (47) for the AI signal. Complementarity in acquisition therefore arises at stable trading equilibria, including the unique one when the variance of noise trading is large enough. The economic force has precedents. In Ganguli and Yang (2009, Section 5), traders can buy a signal about supply together with a signal about the payoff; the supply signal helps them interpret the price, and acquisition can be a complement. The setting differs from the one here: the AI users are retail investors who acquire no information about the payoff, and the information about supply that they obtain is pooled from the disclosures of investors like themselves and covers only the endowment shock, not noise trading. In Farboodi and Veldkamp (2020), data

about other investors' demand are worth more when prices are more informative, so that demand analysis begets demand analysis. In Marmora and Rytchkov (2018), investors may learn about noise rather than fundamentals, and such learning raises price informativeness. What the present model adds is the separation of the two layers of complementarity: the AI provides supply information only, noise trading bounds the complementarity in use, and when the variance of noise trading is large enough the trading equilibrium is unique and stable at every adoption rate while the complementarity in acquisition survives. None of the ingredients the literature has relied on is needed: preferences are CARA, payoffs are normal, there is a single fundamental and a single round of trading, and neither the cost nor the precision of the AI signal depends on how many use it.

What depends on noise trading. Several results rest on the noise trading that nobody observes, and it is useful to separate them from those that do not. Without noise trading ($\tau_\omega \to \infty$), Φ in (28) is the constant $\frac{\tau_u+\tau_\nu+\tau_\xi}{\tau_u+\tau_\nu}$, so the value of AI rises with price informativeness at every stable trading equilibrium, and adoption is a complement there. The complementarity itself therefore does not depend on noise trading. Three groups of results do. First, the limit of the complementarity: the threshold b^* in Proposition 4, the single-peaked value of AI, the substitutability of a perfectly precise AI, and the possibility that the high-adoption equilibrium of Proposition 6 is interior. Second, existence and uniqueness at the trading stage: noise trading bounds the precision of price information at C, so that a linear equilibrium exists for all parameters (Proposition 1(iii)) and is unique under (38); without it, a linear equilibrium exists only for some parameters, and where it exists there are generically two (Remark 1; Manzano and Vives, 2011), so that multiplicity in adoption could not be separated from multiplicity at the trading stage. The same bound underlies Proposition 2, because a precise AI user's trading on supply information stays close to the bound whatever she expects. Third, the price effects on flows that the AI does not observe: Proposition 3(iii) concerns the price impact of noise trading.

6.4 Self-Fulfilling Adoption

With a common cost c, an interior adoption rate λ^* is an equilibrium if $G_A(\lambda^*) = c$, and it is stable if G_A crosses the cost from above: a few additional adopters lower the value of AI below its cost, and they leave again.

Proposition 6 (Multiple adoption equilibria with a unique trading equilibrium)**.** *Suppose that* $8\gamma^2 > \alpha\tau_\epsilon\tau_\omega$*, so that the trading equilibrium is unique and stable at every adoption rate, and that (47) holds strictly in the economy without AI. Then* $\max_\lambda G_A(\lambda) > G_A(0)$*, and for every common cost* $c \in \big(G_A(0), \max_\lambda G_A(\lambda)\big)$ *there are at least three adoption equilibria: no adoption, which is stable; an interior equilibrium* λ_1*, which is unstable; and a stable equilibrium* $\lambda_2 \in (\lambda_1, 1]$*.*

Proof. See Appendix B.7. □

Intuition. In Grossman and Stiglitz (1980), the equilibrium fraction of informed investors is unique because the value of information falls as more investors acquire it, so the value crosses the cost once, from above; the same holds for payoff information here (Proposition 5). The value of AI instead rises with adoption up to the peak of Proposition 4 and falls thereafter. For a cost between the value of AI without adoption and its peak, it therefore crosses the cost twice, from below at λ_1 and from above at λ_2, and no adoption is an equilibrium as well, because the value of AI is below its cost when nobody uses it. The equilibria are self-fulfilling expectations about the price. If investors expect few others to adopt, they expect a price that contains little information about the payoff; interpreting such a price better is not worth the cost of AI, so few adopt, and the price is indeed uninformative. If they expect many others to adopt, they expect an informative price; interpreting it better is worth the cost, so many adopt, and the price is indeed informative. The multiplicity is in the market for AI, not in the asset market: under the condition of the proposition, the asset market has a unique equilibrium at each adoption rate. The structure is that of a participation game, as in Allen and Gale (1994), in which entering a market is worthwhile when others enter; here using a shared technology is worthwhile when others use it, because their use makes the price worth interpreting. Endogenous participation can also affect what the price aggregates more

directly (Lauermann and Wolinsky, 2022); here adoption changes what the price contains only through investors' trading.

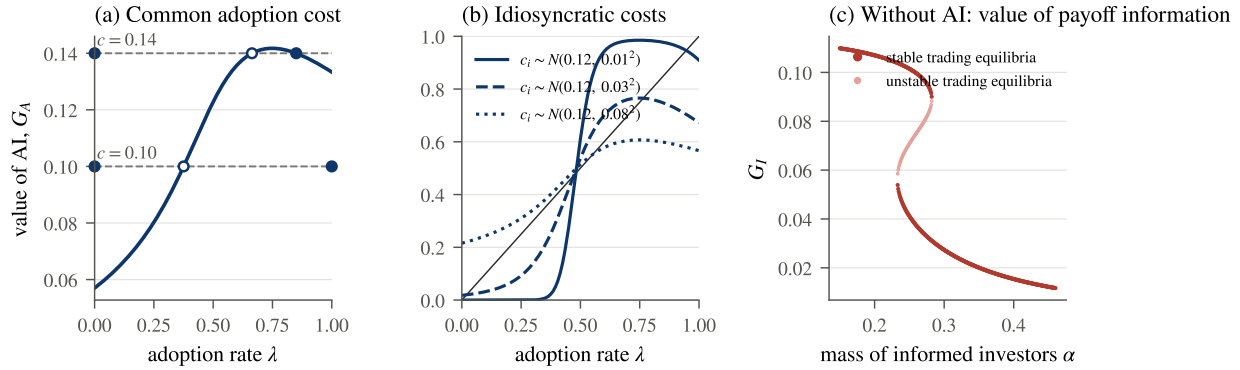


Figure 5: Equilibria in the market for information. Panels (a) and (b) use the parameters of the left panel of Figure 4. (a) Value of AI and two common costs; filled dots are stable adoption equilibria and hollow dots unstable ones. (b) Idiosyncratic normal costs with three levels of dispersion; adoption equilibria are the intersections with the diagonal. (c) The parameters of Figure 2 without AI: the value of the payoff signal along the branches of trading equilibria as the mass of informed investors varies.

Panel (a) of Figure 5 illustrates Proposition 6. Panel (b) illustrates idiosyncratic costs. With little dispersion, the three equilibria survive. With enough dispersion, the fraction of adopters $F_c(G_A(\lambda))$ rises less than one for one with the adoption rate, heterogeneity dominates the complementarity, and the equilibrium is unique. Heterogeneity in costs stands in for any heterogeneity in how investors value a given gain in precision, including differences in risk preferences, which are substantial across investors (Rieger, Wang, and Hens, 2015).

6.5 Conditions for the Complementarity

Three conditions are needed for the complementarity in adoption, and each has a clear interpretation.

An AI of intermediate precision. A perfectly precise AI gives its user price information of the maximal precision C whatever others do, so others' adoption cannot improve what she knows. It does improve what non-users know, because it makes the price more informative. The value of a perfectly precise AI therefore falls with adoption (dotted lines in Figure 4), and adoption is a substitute. A very imprecise AI, at the other end, adds little whatever the

price reveals, so its value changes little with adoption. In between, the threshold b^* in (45) rises with the precision of the AI signal, so the condition for complementarity becomes harder to satisfy as the AI becomes more precise. Together with Proposition 2, this gives a simple picture of technological progress. An AI of intermediate precision, good enough to matter but not good enough to make its users independent of what the price reveals, is the one whose value depends on how many others use it, and it can create multiplicity in adoption. As the AI becomes more precise, it removes multiplicity at the trading stage (Proposition 2) and eventually also the complementarity in adoption. What remains is the amplification of Section 5: a more informative market in which the flows that the AI does not observe move prices more.

A price far from its maximal precision. By Proposition 4, the complementarity needs the variance of noise trading to be small enough that the bound is high, but, under the maintained condition, not so small that the trading stage itself has several equilibria. By (50), the complementarity is also easier to guarantee when the variance of the endowment shock is large and own endowments are imprecise signals of it, so that $\tau_u + \tau_\nu$ is small, because the price without AI is then particularly uninformative.

Informed trading that does not adjust fully. By Proposition 4(iii), adoption lowers the value of becoming informed. If informed investors exit as AI spreads, the bound $\beta_\omega^2 \tau_\omega$ falls and the complementarity weakens.

7 Empirical Implications

The model is motivated by retail-facing AI tools, and its objects map into brokerage and market data. The cleanest sources of variation in adoption are the events described in Section 2: the staggered opening of brokerage platforms to AI assistants, changes in their pricing, free trials, default placement of the assistant in the trading application, and outages of the assistants themselves. Retail order imbalances can be measured from trade data (Boehmer, Jones, Zhang, and Zhang, 2021) or from broker records, and price impact at the order level with the methods of Hautsch and Huang (2012). Inferring informed trading from

order flow is delicate (Aktas, de Bodt, Declerck, and Van Oppens, 2007; Collin-Dufresne and Fos, 2015), which is why the predictions below are stated in terms of ratios of price responses rather than levels.

Prediction 1: Price impact of the order flow of AI users. Where adoption is higher, a retail order imbalance unrelated to fundamentals moves the price less relative to the price response to news, and typically also in absolute terms, so the subsequent reversal is smaller. This applies to the flow of investors whose positions the service observes.

Prediction 2: Price impact of other flows. Adoption raises the price impact of flows that do not pass through the service, such as flow-induced trading by mutual funds or index reconstitution trades, in the same proportion as it raises the price response to fundamental news. The ratio of the two is unaffected by adoption (Proposition 3(iii)), whereas more informed trading lowers it. The prediction therefore separates AI adoption from an increase in informed trading, and index-rebalancing events, which are large and predictable non-platform flows, offer a natural laboratory.

Prediction 3: Price informativeness. Adoption raises price informativeness, measured by the ability of prices to forecast future cash flows (Bai, Philippon, and Savov, 2016), and raises the share of nonfundamental volatility explained by flows outside the service. This differs from a prediction about total volatility: the price impact of platform flow can fall while fundamental-news sensitivity rises.

Prediction 4: Complementarity in adoption. The value of the service to an investor, measured by willingness to pay, retention after free trials, or usage intensity, can rise with adoption by other investors in the same securities. The effect is stronger in securities whose prices are dominated by the order flow of the service's users rather than by other flows, and it flattens or reverses when adoption is widespread.

Prediction 5: Discrete changes in adoption. Common shocks to the cost or quality of AI services, such as fee changes, outages, or restrictions on the use of users' conversations,

produce large and discontinuous changes in adoption. Such changes come with discrete changes in the price impacts and informativeness of Predictions 1 to 3. The outage evidence in He (2026, Section 4.4), in which retail order flow is less correlated and carries a lower price impact during unexpected ChatGPT outages, is a first look at this margin.

Prediction 6: Crowding out of informed trading. Adoption lowers the value of fundamental information. Over horizons long enough for informed capital to adjust, high adoption is associated with less fundamental research, for instance less analyst coverage or lower ownership by active funds, and the complementarity in adoption weakens.

Two cautions follow from the model. First, higher price informativeness is not evidence that exposure to nonfundamental shocks has fallen; the two move in opposite directions for flows that bypass the AI. Second, the fragility that AI creates here does not originate in the technology's errors, which are user-specific and diversify away, but in the market's greater reliance on its price. Empirical tests should therefore examine how the price impact of non-platform flow changes with adoption, not only adoption rates.

8 Policy Implications

The analysis carries several implications for the regulation of AI services in retail investing. A first implication concerns the object of supervision. The concern of financial-stability authorities is that many investors who rely on the same tool act alike (Section 2). In the model, this correlated behavior is not a shared error, and it does not disappear when the technology improves. It is the rational response of many investors to the same improvement in their interpretation of the price, and its effect on the market is twofold: prices become more informative, and the price impact of the flows that the AI does not observe rises in the same proportion as the price response to fundamentals. Supervisors who monitor price informativeness alone will therefore see an improvement where exposure to nonfundamental shocks has risen. The relevant statistic is the price impact of flows that bypass the AI, such as index rebalancing or flow-induced trading by funds, relative to the price response to fundamental news.

A second implication concerns the use of investors' data. The value of the AI service rests on its ability to pool what its users disclose. Restrictions on the retention or pooling of conversations, of the kind that privacy rules and the training policies of providers govern (Section 2), lower the precision of the AI signal. Because adoption has multiple equilibria, a modest restriction can have a large effect: if it moves the value of AI below the level that sustains the high-adoption equilibrium, adoption collapses and price informativeness falls discretely. The same applies to outages and to losses of trust in the service. A restriction that lowers the precision of the AI signal also works in the opposite direction at the trading stage: by Proposition 2, a precise AI held by enough investors removes multiplicity there, so making the AI less precise can reintroduce it in markets where the variance of noise trading is small.

A third implication concerns the pricing and placement of AI services by brokers. Because adoption is a coordination game, free access, default placement in the trading application, and integration into the order flow are instruments for selecting the high-adoption equilibrium. Brokers who offer such services have an incentive to use them, and the resulting adoption raises price informativeness. The model does not provide a welfare ranking of the equilibria, because it has no real decision that depends on the price; the trade-off between more informative prices and a larger exposure to unobserved flows is left to future work (Section 9).

Finally, the distinction between the flows that the AI observes and those that it does not suggests that the fragility identified here is more pronounced when adoption is concentrated in a few services and when a large share of order flow originates outside them. Several providers with user-specific errors do not change the uniqueness of the trading equilibrium, but a common error across users would, and the concentration of retail investors on a small number of models is the natural setting for such errors.

9 Limitations and Future Research

The model abstracts from several features of the environment it describes. The AI service makes no error that is common to its users. If the service's assessment of the endowment shock carried a common error, AI users would trade on it, it would enter aggregate demand

in proportion to the mass of AI users, and the price would load on a fourth shock that only AI users can learn about. The AI would then be a source of nonfundamental shocks in its own right, which is the concern that the literature on technological monocultures raises, from crowding among algorithmic traders that use the same signals (Kozhan and Tham, 2012) to the systemic cost of institutions becoming alike (Wagner, 2010, 2011; Financial Stability Board, 2024), and the market's exposure to this shock would rise with adoption. The present results isolate the part of the fragility that survives when the technology makes no common error: it originates in the market's greater reliance on its price, not in errors of the technology. The extension to common errors is the natural route to studying technological monocultures.

The model stops at prices. The natural extension adds a firm or capital provider that observes p and makes a real decision, as in Goldstein, Ozdenoren, and Yuan (2013) and the literature on the real effects of prices. The amplified price impact of unseen flow would then distort a real allocation, and Proposition 3(iii) would acquire a welfare interpretation it lacks here. A full welfare treatment would weigh informed investors' rents, retail investors' certainty equivalents, adoption costs, and any real effects of price informativeness.

The analysis is static. Adoption is decided once, before trading, and the AI signal is drawn once. In practice adoption spreads over time, users accumulate experience with the service, and the service accumulates data. A dynamic version of the model would allow the trading complementarity and the adoption complementarity to interact over time.

Despite these limitations, the central mechanism, that information about supply multiplies the precision of price information and thereby makes the acquisition of such information a strategic complement at stable trading equilibria, depends on none of them.

10 Conclusion

When public information is already reflected in prices, an AI that learns only from public data cannot tell investors anything about fundamentals beyond what the price reflects. An AI service with many users can learn something else: from what its users disclose about their own positions, it learns the part of supply that is unrelated to fundamentals, which is precisely what keeps the price from revealing them. This paper studies the value of such

signals, the incentives to acquire them, and their effects on prices.

The analysis can be summarized in terms of precisions. The price is a signal of the payoff with precision τ_p; an investor who uses her endowment to remove part of the supply noise interprets it with precision $\tau_p + \tau_2$; an AI user removes more of the noise and interprets it with precision $\tau_p + \tau_2^A$, a multiple of the former. The AI is not a second forecast of the payoff. It is a technology for recovering information that is already in the price but obscured by supply. Three results follow. First, the value of such a technology can rise with price informativeness, because its multiplier applies to a larger base, until the price approaches the bound that noise trading sets. Second, since others' adoption makes the price more informative, the acquisition of AI signals can be a strategic complement at stable trading equilibria, where in the same model information about the payoff is a substitute, and the market for AI can have multiple stable equilibria even when the asset market has a unique one. Small changes in the cost or quality of AI, or in what investors expect of each other, then move adoption, price informativeness, and the price impact of order flow discretely.

The broader implication is that an information technology in financial markets should be evaluated not only by the accuracy of its standalone predictions, but by the precision that it recovers from market signals and by how much it raises the market's exposure to the flows that nobody observes.

References

Admati, A. R., and P. Pfleiderer. 1986. A monopolistic market for information. *Journal of Economic Theory* 39:400–438.

Admati, A. R., and P. Pfleiderer. 1990. Direct and indirect sale of information. *Econometrica* 58:901–28.

Ahnert, T., and C.-P. Georg. 2018. Information contagion and systemic risk. *Journal of Financial Stability* 35:159–71.

Ahnert, T., P. Hoffmann, and C. Monnet. 2025. Payments and privacy in the digital economy. *Journal of Financial Economics* 169:104050.

Ahnert, T., and A. Kakhbod. 2017. Information choice and amplification of financial crises. *Review*

of Financial Studies 30:2130–78.

Aktas, N., E. de Bodt, F. Declerck, and H. Van Oppens. 2007. The PIN anomaly around M&A announcements. *Journal of Financial Markets* 10:169–91.

Allen, F., and D. Gale. 1994. Limited market participation and volatility of asset prices. *American Economic Review* 84:933–55.

Allen, F., and D. Gale. 2000. Financial contagion. *Journal of Political Economy* 108:1–33.

Allen, F., and D. Gale. 2004. Financial fragility, liquidity, and asset prices. *Journal of the European Economic Association* 2:1015–48.

Allen, F., S. Morris, and H. S. Shin. 2006. Beauty contests and iterated expectations in asset markets. *Review of Financial Studies* 19:719–52.

Andrei, D., J. Cujean, and M. Wilson. 2023. The lost capital asset pricing model. *Review of Economic Studies* 90:2703–62.

Bai, J., T. Philippon, and A. Savov. 2016. Have financial markets become more informative? *Journal of Financial Economics* 122:625–54.

Bank of England. 2025. Financial stability in focus: Artificial intelligence in the financial system. Report, Bank of England, April.

Barber, B. M., X. Huang, T. Odean, and C. Schwarz. 2022. Attention-induced trading and returns: Evidence from Robinhood users. *Journal of Finance* 77:3141–90.

Barlevy, G., and P. Veronesi. 2000. Information acquisition in financial markets. *Review of Economic Studies* 67:79–90.

Bauer, K., C. M. Damm, F. Hett, and L. Pelizzon. 2026. The double-edged mind: How LLMs expand stock market participation yet strengthen confirmation-seeking. SAFE Working Paper 480, Leibniz Institute for Financial Research SAFE, April.

Bhattacharya, U., A. Hackethal, S. Kaesler, B. Loos, and S. Meyer. 2012. Is unbiased financial advice to retail investors sufficient? Answers from a large field study. *Review of Financial Studies* 25:975–1032.

Blankespoor, E., J. Croom, and S. M. Grant. 2026. Generative AI and investor processing of financial information. *Journal of Accounting and Economics* 82:101908.

Boehmer, E., C. M. Jones, X. Zhang, and X. Zhang. 2021. Tracking retail investor activity. *Journal of Finance* 76:2249–305.

Bolton, P., X. Freixas, and J. Shapiro. 2007. Conflicts of interest, information provision, and competition in the financial services industry. *Journal of Financial Economics* 85:297–330.

Boot, A., P. Hoffmann, L. Laeven, and L. Ratnovski. 2021. Fintech: What's old, what's new? *Journal of Financial Stability* 53:100836.

Börner, L., and J. W. Hatfield. 2017. The design of debt-clearing markets: Clearinghouse mechanisms in preindustrial Europe. *Journal of Political Economy* 125:1991–2037.

Cartea, Á., P. Chang, and J. Penalva. 2022. Algorithmic collusion in electronic markets: The impact of tick size. Working Paper, University of Oxford, October.

Cartea, Á., J.-E. Colliard, T. Foucault, P. Hoffmann, R. Graumans, and J.-D. Sigaux. 2026. Artificial intelligence and financial markets. ECB Discussion Paper 32, European Central Bank, September.

Choukhmane, T., T. de Silva, W. Lin, and M. Akuzawa. 2026. AI financial advice: Supply, demand, and life cycle implications. NBER Working Paper 35574, National Bureau of Economic Research, August.

Cipriani, M., and A. Guarino. 2014. Estimating a structural model of herd behavior in financial markets. *American Economic Review* 104:224–51.

Colliard, J.-E., T. Foucault, and S. Lovo. Forthcoming. Algorithmic pricing and liquidity in securities markets. *Review of Financial Studies*.

Collin-Dufresne, P., and V. Fos. 2015. Do prices reveal the presence of informed trading? *Journal of Finance* 70:1555–82.

D'Acunto, F., N. Prabhala, and A. G. Rossi. 2019. The promises and pitfalls of robo-advising. *Review of Financial Studies* 32:1983–2020.

Daníelsson, J., R. Macrae, and A. Uthemann. 2022. Artificial intelligence and systemic risk. *Journal of Banking & Finance* 140:106290.

Dávila, E., and C. Parlatore. 2023. Volatility and informativeness. *Journal of Financial Economics* 147:550–72.

Diamond, D. W., and R. E. Verrecchia. 1981. Information aggregation in a noisy rational expectations economy. *Journal of Financial Economics* 9:221–35.

Dou, W. W., I. Goldstein, and Y. Ji. 2025. AI-powered trading, algorithmic collusion, and price efficiency. NBER Working Paper 34054, National Bureau of Economic Research, July.

Dou, W. W., I. Goldstein, and Y. Ji. 2026. Financial market fragility in the era of AI planning.

Working Paper, The Wharton School, University of Pennsylvania, September.

Dow, J., I. Goldstein, and A. Guembel. 2017. Incentives for information production in markets where prices affect real investment. *Journal of the European Economic Association* 15:877–909.

Eisfeldt, A. L., and G. Schubert. 2025. Generative AI and finance. *Annual Review of Financial Economics* 17:363–93.

ESMA. 2024. Public statement on the use of artificial intelligence (AI) in the provision of retail investment services. Public Statement ESMA35-335435667-5924, European Securities and Markets Authority, May.

Fama, E. F. 1970. Efficient capital markets: A review of theory and empirical work. *Journal of Finance* 25:383–417.

Farboodi, M., and L. Veldkamp. 2020. Long-run growth of financial data technology. *American Economic Review* 110:2485–523.

Fedyk, A., A. Kakhbod, P. Li, and U. Malmendier. 2026. AI and perception biases in investments: An experimental study. *Journal of Financial Economics* 185:104350.

Financial Stability Board. 2024. The financial stability implications of artificial intelligence. Report, Financial Stability Board, November.

FINRA. 2024. FINRA reminds members of regulatory obligations when using generative artificial intelligence and large language models. Regulatory Notice 24-09, Financial Industry Regulatory Authority, June.

FINRA Investor Education Foundation. 2024. The machines are coming (with personal finance information). Do we trust them? Consumer Insights: Money & Investing, FINRA Investor Education Foundation, May.

Foucault, T., and T. Gehrig. 2008. Stock price informativeness, cross-listings, and investment decisions. *Journal of Financial Economics* 88:146–68.

Froot, K. A., D. S. Scharfstein, and J. C. Stein. 1992. Herd on the street: Informational inefficiencies in a market with short-term speculation. *Journal of Finance* 47:1461–84.

Galema, R., and D. Gerritsen. 2019. The effect of the accidental disclosure of confidential short sales positions. *Finance Research Letters* 28:87–94.

Ganguli, J. V., and L. Yang. 2009. Complementarities, multiplicity, and supply information. *Journal of the European Economic Association* 7:90–115.

García, D., and G. Strobl. 2011. Relative wealth concerns and complementarities in information acquisition. *Review of Financial Studies* 24:169–207.

Gennaioli, N., A. Shleifer, and R. Vishny. 2012. Neglected risks, financial innovation, and financial fragility. *Journal of Financial Economics* 104:452–68.

Gennotte, G., and H. Leland. 1990. Market liquidity, hedging, and crashes. *American Economic Review* 80:999–1021.

Gerritsen, D., and A. de Regt. 2025. Influencers and consumer financial decision-making. *International Journal of Consumer Studies* 49:e70037.

Goldstein, I., C. Huang, and L. Yang. 2025. Fragility of financial markets. *Annual Review of Financial Economics* 17:27–48.

Goldstein, I., E. Ozdenoren, and K. Yuan. 2013. Trading frenzies and their impact on real investment. *Journal of Financial Economics* 109:566–82.

Goldstein, I., and A. Pauzner. 2005. Demand–deposit contracts and the probability of bank runs. *Journal of Finance* 60:1293–327.

Goldstein, I., and L. Yang. 2015. Information diversity and complementarities in trading and information acquisition. *Journal of Finance* 70:1723–65.

Goodhart, C. A. E., P. Sunirand, and D. P. Tsomocos. 2006. A model to analyse financial fragility. *Economic Theory* 27:107–42.

Greig, F., T. Ramadorai, A. G. Rossi, S. P. Utkus, and A. Walther. 2025. Human financial advice in the age of automation. Working Paper, Imperial College London, July.

Gropp, R., H. Hakenes, and I. Schnabel. 2011. Competition, risk-shifting, and public bail-out policies. *Review of Financial Studies* 24:2084–120.

Grossman, S. 1976. On the efficiency of competitive stock markets where trades have diverse information. *Journal of Finance* 31:573–85.

Grossman, S. J., and J. E. Stiglitz. 1980. On the impossibility of informationally efficient markets. *American Economic Review* 70:393–408.

Hau, H., Y. Huang, C. Lin, H. Shan, Z. Sheng, and L. Wei. 2024. FinTech credit and entrepreneurial growth. *Journal of Finance* 79:3309–59.

Hautsch, N., and R. Huang. 2012. The market impact of a limit order. *Journal of Economic Dynamics and Control* 36:501–22.

He, X. 2026. When ChatGPT stops talking: GenAI, retail trading coordination, and market liquidity. Working Paper, Lancaster University, September.

Hellwig, C., and L. Veldkamp. 2009. Knowing what others know: Coordination motives in information acquisition. *Review of Economic Studies* 76:223–51.

Hellwig, M. F. 1980. On the aggregation of information in competitive markets. *Journal of Economic Theory* 22:477–98.

Inderst, R., and M. Ottaviani. 2009. Misselling through agents. *American Economic Review* 99:883–908.

International Monetary Fund. 2024. Advances in artificial intelligence: Implications for capital market activities. In *Global Financial Stability Report: Steadying the course: Uncertainty, artificial intelligence, and financial stability*, chap. 3. Washington, DC: International Monetary Fund.

Kacperczyk, M., J. Nosal, and S. Sundaresan. 2025. Market power and price informativeness. *Review of Economic Studies* 92:1955–86.

Kelly, B., S. Malamud, and K. Zhou. 2024. The virtue of complexity in return prediction. *Journal of Finance* 79:459–503.

Kozhan, R., and W. W. Tham. 2012. Execution risk in high-frequency arbitrage. *Management Science* 58:2131–49.

Laudenbach, C., M. Ungeheuer, and M. Weber. 2023. How to alleviate correlation neglect in investment decisions. *Management Science* 69:3400–3414.

Lauermann, S., and A. Wolinsky. 2022. A common-value auction with state-dependent participation. *Theoretical Economics* 17:841–81.

Leippold, M., Q. Wang, and W. Zhou. 2022. Machine learning in the Chinese stock market. *Journal of Financial Economics* 145:64–82.

Leitner, G., J. Singh, A. van der Kraaij, and B. Zsámboki. 2024. The rise of artificial intelligence: Benefits and risks for financial stability. *ECB Financial Stability Review*, May, special feature.

Lopez-Lira, A., and Y. Tang. 2026. Can ChatGPT forecast stock price movements? Return predictability and large language models. *Journal of Financial Economics* 184:104335.

Manzano, C., and X. Vives. 2011. Public and private learning from prices, strategic substitutability and complementarity, and equilibrium multiplicity. *Journal of Mathematical Economics* 47:346–69.

Marmora, P., and O. Rytchkov. 2018. Learning about noise. *Journal of Banking & Finance* 89:209–24.

Mele, A., and F. Sangiorgi. 2015. Uncertainty, information acquisition, and price swings in asset markets. *Review of Economic Studies* 82:1533–67.

Menkveld, A. J. 2013. High frequency trading and the new market makers. *Journal of Financial Markets* 16:712–40.

Menkveld, A. J., and M. A. Zoican. 2017. Need for speed? Exchange latency and liquidity. *Review of Financial Studies* 30:1188–228.

Ottaviani, M., and P. N. Sørensen. 2015. Price reaction to information with heterogeneous beliefs and wealth effects: Underreaction, momentum, and reversal. *American Economic Review* 105:1–34.

Rathi, N. 2026. Oral evidence: Work of the Financial Conduct Authority, HC 6. House of Commons Treasury Committee, October 13, Q767.

Rieger, M. O., M. Wang, and T. Hens. 2015. Risk preferences around the world. *Management Science* 61:637–48.

Rindi, B. 2008. Informed traders as liquidity providers: Anonymity, liquidity and price formation. *Review of Finance* 12:497–532.

Rochet, J.-C., and X. Vives. 2004. Coordination failures and the lender of last resort: Was Bagehot right after all? *Journal of the European Economic Association* 2:1116–47.

Rossi, A. G., and S. Utkus. 2024. The diversification and welfare effects of robo-advising. *Journal of Financial Economics* 157:103869.

Shapiro, J., and D. Skeie. 2015. Information management in banking crises. *Review of Financial Studies* 28:2322–63.

Veldkamp, L. L. 2006. Media frenzies in markets for financial information. *American Economic Review* 96:577–601.

Verrecchia, R. E. 1982. Information acquisition in a noisy rational expectations economy. *Econometrica* 50:1415–30.

Vives, X. 2008. *Information and learning in markets: The impact of market microstructure*. Princeton, NJ: Princeton University Press.

Wagner, W. 2010. Diversification at financial institutions and systemic crises. *Journal of Financial Intermediation* 19:373–86.

Wagner, W. 2011. Systemic liquidation risk and the diversity–diversification trade-off. *Journal of Finance* 66:1141–75.

Welch, I. 2022. The wisdom of the Robinhood crowd. *Journal of Finance* 77:1489–527.

Weller, B. M. 2018. Does algorithmic trading reduce information acquisition? *Review of Financial Studies* 31:2184–226.

Yang, L., and H. Zhu. 2020. Back-running: Seeking and hiding fundamental information in order flows. *Review of Financial Studies* 33:1484–533.

A Notation

B Derivations and Proofs

B.1 Proof of Proposition 1

Market clearing and coefficient matching (parts i–ii). The argument is simplest if we separate the precision of price information from the mass of each investor type. Put

$$m = (1-\alpha)\lambda, \quad P_U = \tau_p + \tau_2, \quad P_A = \tau_p + \tau_2^A, \quad \theta_U = \frac{\tau_\nu}{\tau_u + \tau_\nu}, \quad \theta_A = \frac{\tau_\nu + \tau_\xi}{\tau_u + \tau_\nu + \tau_\xi},$$

and define the aggregate price-information precision and the aggregate supply-information response by

$$B = (1-m)P_U + mP_A, \qquad H = (1-m)\theta_U P_U + m\theta_A P_A.$$

The mass of informed investors is included in the weight $1-m$ because they use the same supply information as non-users. Informed investors' payoff signals contribute $\alpha\tau_\epsilon v$ to aggregate demand. Idiosyncratic errors average out. Using the individual demands in Section 4 and the identities (23) and (30), we obtain

$$\gamma \int_0^1 x_i \, di = \left(\frac{B}{A_v} - \tau_v - \alpha\tau_\epsilon - B \right) p + \alpha\tau_\epsilon v - (\gamma - \beta_u^{-1} H) u. \tag{51}$$

Clearing the market, $\int x_i \, di = \omega$, gives

$$p = \frac{\alpha\tau_\epsilon v - (\gamma - \beta_u^{-1} H) u - \gamma\omega}{\tau_v + \alpha\tau_\epsilon + B - B/A_v}. \tag{52}$$

Matching the coefficient on v with the conjectured linear price yields $A_v(\tau_v + \alpha\tau_\epsilon + B) - B = \alpha\tau_\epsilon$, hence

$$A_v = \frac{\alpha\tau_\epsilon + B}{\tau_v + \alpha\tau_\epsilon + B} \in (0,1). \tag{53}$$

The denominator in (52) is therefore $\alpha\tau_\epsilon / A_v > 0$. Taking ratios of its remaining coefficients gives

$$\beta_\omega = \frac{\alpha\tau_\epsilon}{\gamma}, \qquad \beta_u^{-1} = \frac{\gamma - \beta_u^{-1} H}{\alpha\tau_\epsilon}. \tag{54}$$

Symbol	Meaning
v, τ_v	Payoff of the risky asset and its prior precision
u, τ_u	Aggregate endowment shock and its precision
$u_i = u + \nu_i$, τ_ν	Investor i's endowment and the precision of its idiosyncratic component
ω, τ_ω	Supply of noise traders and its precision
$s_i = v + \epsilon_i$, τ_ϵ	Payoff signal of an informed investor and its precision
$r_i = u + \xi_i$, τ_ξ	AI signal and its precision
α; λ	Mass of informed investors; adoption rate among retail investors
γ	Coefficient of absolute risk aversion
A_v, A_u, A_ω	Price response to the payoff and price impacts of the endowment shock and of noise trading
β_u^{-1}, β_ω^{-1}	Price impacts of the endowment shock and of noise trading relative to the response to the payoff
τ_p	Price informativeness: precision of the price as a signal of the payoff
$\tau_p + \tau_2$, $\tau_p + \tau_2^A$	Precision of the price information of an investor without AI and of an AI user
Φ	Factor by which the AI multiplies the precision of price information, (28)
$\beta_\omega^2 \tau_\omega$	Ceiling on these precisions, attained by an investor who knows u
τ_U, τ_A, τ_I	Posterior precisions of a retail investor without AI, an AI user, and an informed investor
K	Market's average posterior precision beyond the prior; $A_v = K/(\tau_v + K)$
f_λ	Aggregate best response
G_A, G_I	Certainty-equivalent values of the AI signal and of the payoff signal
z_1, z_{2i}, z_{2i}^A	Independent signals of the payoff derived from the price and the supply signal
ζ_p, ζ_{2i}, ζ_{2i}^A	Errors of these signals; ζ_p is the price noise
δ_u	Weight on the supply signal that makes z_{2i} independent of z_1
$u_i^A = u + \nu_i^A$	Combined supply signal of an AI user and its noise
ρ^2	Share of the price noise explained by an investor's supply information
Appendix only	
D_A, D_I	Derivatives with respect to the mass of AI users and of informed investors, holding the other fixed

The latter identity is equivalently

$$\beta_u^{-1}\big(\alpha\tau_\epsilon + H\big) = \gamma, \tag{55}$$

or, using the definition of H,

$$\beta_u = f_\lambda(\beta_u) = \frac{1}{\gamma}\left[\alpha\tau_\epsilon + (1-m)\theta_U P_U + m\theta_A P_A\right]. \tag{56}$$

Substitute P_U and P_A from (19) and (26), with $\beta_\omega = \alpha\tau_\epsilon/\gamma$. This is precisely the fixed-point equation (33). It also proves the price-coefficient formulas (35).

For existence and uniqueness it is useful to set $b = \beta_u^{-1}$ and $D = \gamma^2/(\alpha^2\tau_\epsilon^2\tau_\omega)$. Then (55) becomes the single scalar equation

$$\underbrace{\alpha\tau_\epsilon b + (1-m)\frac{\tau_\nu b}{b^2 + D(\tau_u+\tau_\nu)} + m\frac{(\tau_\nu+\tau_\xi)b}{b^2 + D(\tau_u+\tau_\nu+\tau_\xi)}}_{h_\lambda(b)} = \gamma. \tag{57}$$

Existence and bounds (part iii). The continuous function h_λ has $h_\lambda(0) = 0$ and $h_\lambda(b) \geq \alpha\tau_\epsilon b \to \infty$ as $b \to \infty$, so it attains γ at some $b > 0$. It cannot attain γ at $b \leq 0$, where every term is nonpositive. At any positive solution both fractions are strictly positive, so

$$0 < b < \frac{\gamma}{\alpha\tau_\epsilon} = \beta_\omega^{-1}.$$

In terms of the best response, this is the existence argument of Manzano and Vives (2011): $f_\lambda(0) = \frac{\alpha\tau_\epsilon}{\gamma} > 0$ and, since $P_U, P_A < D^{-1}$, f_λ is bounded, so $f_\lambda(\beta) - \beta < 0$ for large β.

Uniqueness (part iv). The two conditions mirror Proposition 3 of Manzano and Vives (2011). Their first condition, strategic substitutability $f' < 0$, has no counterpart here: by (59) below, $f'_\lambda > 0$ at every conjecture, because informed investors' payoff signals have independent errors, so that the weight they put on them does not depend on the price; this is the case $\rho = 0$ in their notation. Their second condition bounds the slope of the best response by its maximum over conjectures, and its counterpart is (36). Writing $T_U = \tau_u + \tau_\nu$ and $T_A = \tau_u + \tau_\nu + \tau_\xi$, (19) and (26) give $\theta_k P_k = \frac{\tau_k^s \beta_u^2}{1 + D T_k \beta_u^2}$ with $\tau_U^s = \tau_\nu$ and $\tau_A^s = \tau_\nu + \tau_\xi$, so

that differentiating (56) gives

$$f'_\lambda(\beta_u) = \frac{2}{\gamma}\left[(1-m)\tau_\nu\, g_U(\beta_u) + m(\tau_\nu+\tau_\xi)\, g_A(\beta_u)\right], \qquad g_k(\beta) \equiv \frac{\beta}{(1+DT_k\beta^2)^2}.$$

Since $g'_k(\beta) = \frac{1-3DT_k\beta^2}{(1+DT_k\beta^2)^3}$, g_k attains its maximum $\frac{9}{16\sqrt{3DT_k}}$ at $\beta = \frac{1}{\sqrt{3DT_k}}$. Hence, for every $\beta > 0$,

$$f'_\lambda(\beta) \le \frac{9}{8\sqrt{3}\,\gamma\sqrt{D}}\left[(1-m)\frac{\tau_\nu}{\sqrt{T_U}} + m\,\frac{\tau_\nu+\tau_\xi}{\sqrt{T_A}}\right],$$

and since $\frac{1}{\gamma\sqrt{D}} = \frac{\alpha\tau_\epsilon\sqrt{\tau_\omega}}{\gamma^2}$, the right-hand side is below one if and only if (36) holds. Then $f_\lambda(\beta) - \beta$ is strictly decreasing, from $\frac{\alpha\tau_\epsilon}{\gamma} > 0$ to $-\infty$, so it vanishes exactly once, at a point where $f'_\lambda < 1$.

For (37), note that for $x, y > 0$,

$$\frac{d}{db}\frac{xb}{b^2+y} = \frac{x(y-b^2)}{(b^2+y)^2} \ge -\frac{x}{8y},$$

with equality only at $b^2 = 3y$. Consequently

$$h'_\lambda(b) \ge \alpha\tau_\epsilon - \frac{\alpha^2\tau_\epsilon^2\tau_\omega}{8\gamma^2}\left[(1-m)\frac{\tau_\nu}{\tau_u+\tau_\nu} + m\frac{\tau_\nu+\tau_\xi}{\tau_u+\tau_\nu+\tau_\xi}\right].$$

Condition (37) makes this bound nonnegative. Even at equality, the derivative vanishes only at isolated points, so h_λ is strictly increasing and the equilibrium unique. Each fraction in brackets is less than one, giving (38) as the uniform sufficient condition.

Stability and comparative statics. Differentiation of (19) and (26) yields

$$\begin{aligned} \frac{\partial P_U}{\partial \beta_u} &= \frac{2\beta_u^{-3}P_U^2}{\tau_u+\tau_\nu}, & \frac{\partial P_A}{\partial \beta_u} &= \frac{2\beta_u^{-3}P_A^2}{\tau_u+\tau_\nu+\tau_\xi}, \\ \frac{\partial P_U}{\partial \beta_\omega} &= \frac{2\beta_\omega^{-3}P_U^2}{\tau_\omega}, & \frac{\partial P_A}{\partial \beta_\omega} &= \frac{2\beta_\omega^{-3}P_A^2}{\tau_\omega}. \end{aligned} \tag{58}$$

Thus the slope of (56) is

$$f'_\lambda(\beta_u) = \frac{2\beta_u^{-3}}{\gamma}\left[(1-m)\frac{\tau_\nu P_U^2}{(\tau_u+\tau_\nu)^2} + m\frac{(\tau_\nu+\tau_\xi)P_A^2}{(\tau_u+\tau_\nu+\tau_\xi)^2}\right] > 0. \tag{59}$$

Since $h_\lambda(b) = \gamma b f_\lambda(1/b)$, at any equilibrium

$$h'_\lambda(b) = \gamma\beta_u\big(1 - f'_\lambda(\beta_u)\big). \tag{60}$$

A strictly positive derivative of h_λ therefore implies the stability criterion $f'_\lambda < 1$. Under (36) or the strict version of (37) the implicit function theorem also makes b, and hence β_u, differentiable in λ. □

Number of equilibria in general. Clearing the denominators in (57) gives a polynomial of degree five in β_u^{-1}:

$$\begin{aligned}\alpha\tau_\epsilon\beta_u^{-5} - \gamma\beta_u^{-4} + \left[\tau_\nu + (1-\alpha)\lambda\tau_\xi + \frac{(2\tau_u + 2\tau_\nu + \tau_\xi)\gamma^2}{\alpha\tau_\epsilon\tau_\omega}\right]\beta_u^{-3} \\ - \frac{(2\tau_u + 2\tau_\nu + \tau_\xi)\gamma^3}{\alpha^2\tau_\epsilon^2\tau_\omega}\beta_u^{-2} \\ + \left[\frac{(\tau_u + \tau_\nu)(\tau_u + \tau_\nu + \tau_\xi)\gamma^4}{\alpha^3\tau_\epsilon^3\tau_\omega^2} + \frac{\gamma^2\left(\tau_\nu(\tau_u + \tau_\nu + \tau_\xi) + (1-\alpha)\lambda\tau_u\tau_\xi\right)}{\alpha^2\tau_\epsilon^2\tau_\omega}\right]\beta_u^{-1} \\ - \frac{(\tau_u + \tau_\nu)(\tau_u + \tau_\nu + \tau_\xi)\gamma^5}{\alpha^4\tau_\epsilon^4\tau_\omega^2} = 0.\end{aligned} \tag{61}$$

The coefficients alternate in sign, so by Descartes' rule of signs the polynomial has five, three, or one positive roots, counting multiplicity. Replacing β_u^{-1} by $-\beta_u^{-1}$ makes all coefficients negative, so there is no negative root. Every positive root solves (57), because the factors cleared are positive. The polynomial of Manzano and Vives (2011) is also of degree five, but has at most three positive roots (their Proposition 1). Here five can occur: investors with and without AI trade on supply information of different precision, so their purchases against the endowment shock peak at different price impacts, and h_λ can have two local maxima. In terms of the best-response map, uniqueness requires that f_λ cross the diagonal only once. If $f'_\lambda(\beta_u) > 1$ at some equilibrium, f_λ crosses the diagonal from below there, and since $f_\lambda(0) = \frac{\alpha\tau_\epsilon}{\gamma} > 0$ and f_λ is bounded, it must also cross from above at a smaller and at a larger β_u, so that there are at least three equilibria. Conversely, apart from tangencies, which occur only at isolated parameter values, several equilibria require one at which $f'_\lambda > 1$.

Without AI, the factor $\beta_u^{-2} + \frac{(\tau_u+\tau_\nu+\tau_\xi)\gamma^2}{\alpha^2\tau_\epsilon^2\tau_\omega}$ cancels, and the equilibrium solves the cubic

$$\alpha\tau_\epsilon\beta_u^{-3} - \gamma\beta_u^{-2} + \left[\tau_\nu + \frac{\gamma^2(\tau_u+\tau_\nu)}{\alpha\tau_\epsilon\tau_\omega}\right]\beta_u^{-1} - \frac{\gamma^3(\tau_u+\tau_\nu)}{\alpha^2\tau_\epsilon^2\tau_\omega} = 0. \tag{62}$$

which has one or three positive roots and no negative root, as in Manzano and Vives (2011); with three, the extreme ones are stable and the middle one is unstable.

B.2 Proof of Proposition 2

Write $b = \beta_u^{-1}$, $m = (1-\alpha)\lambda$, $C = \alpha^2\tau_\epsilon^2\tau_\omega/\gamma^2 = D^{-1}$, $\bar{b} = \gamma/(\alpha\tau_\epsilon)$, and $y_U = (\tau_u+\tau_\nu)/C$ and $y_A = (\tau_u+\tau_\nu+\tau_\xi)/C$ for the constants in the denominators of (57). By Proposition 1(iii), every equilibrium lies in $(0,\bar{b})$, and $h_\lambda(\bar{b}) > \gamma$.

(i) The proof mirrors that of Corollary 9 in Manzano and Vives (2011): it asks when h'_λ can vanish, which by (60) is when $f'_\lambda = 1$ at an equilibrium. With $\tau_\xi = \infty$, $P_A = C$ and $\theta_A = 1$, so

$$h_\lambda(b) = (\alpha\tau_\epsilon + mC)\,b + \frac{(1-m)\tau_\nu\,b}{b^2+y_U}, \qquad h'_\lambda(b) = \alpha\tau_\epsilon + mC + \frac{(1-m)\tau_\nu\,(y_U-b^2)}{(b^2+y_U)^2}.$$

With $z = b^2$ and $a \equiv \alpha\tau_\epsilon + mC$, $h'_\lambda(b) = 0$ if and only if

$$az^2 + \big[2ay_U - (1-m)\tau_\nu\big]z + ay_U^2 + (1-m)\tau_\nu y_U = 0,$$

a quadratic in z with discriminant $(1-m)\tau_\nu\big[(1-m)\tau_\nu - 8ay_U\big]$. The discriminant is non-positive if and only if

$$(1-m)\,\frac{\tau_\nu}{\tau_u+\tau_\nu} \le 8\Big(m + \frac{\gamma^2}{\alpha\tau_\epsilon\tau_\omega}\Big),$$

which is (40). Then $h'_\lambda \ge 0$ everywhere, with at most one zero, so h_λ is strictly increasing from $h_\lambda(0) = 0$ and equals γ exactly once. The threshold in (40) is below $\frac{\tau_\nu/(\tau_u+\tau_\nu)}{8+\tau_\nu/(\tau_u+\tau_\nu)} < \frac{1}{9}$.

(ii) The proof shows that h_λ is strictly increasing on $(0,\bar{b}]$. The condition on τ_ξ reads $y_A \ge 3\bar{b}^2$. The derivative of the AI users' term, $\frac{x(y_A-b^2)}{(b^2+y_A)^2}$ with $x \equiv m(\tau_\nu+\tau_\xi)$, is decreasing in b

for $b^2 < 3y_A$, so on $(0, \bar{b}]$ it is at least its value at $b^2 = \frac{y_A}{3}$, which is $\frac{3x}{8y_A}$. Since $\frac{\tau_\nu+\tau_\xi}{\tau_u+\tau_\nu+\tau_\xi} \geq \frac{\tau_\nu}{\tau_u+\tau_\nu}$,

$$\frac{3x}{8y_A} = \frac{3}{8}\, m\, \frac{\tau_\nu + \tau_\xi}{\tau_u + \tau_\nu + \tau_\xi}\, C \geq 3m\, \frac{\tau_\nu}{\tau_u + \tau_\nu}\, \frac{C}{8}.$$

The derivative of the term of investors without AI is at least $-(1-m)\frac{\tau_\nu}{\tau_u+\tau_\nu}\frac{C}{8}$ by the proof of part (iv) of Proposition 1. Hence, on $(0, \bar{b}]$,

$$h'_\lambda(b) \geq \alpha\tau_\epsilon + \frac{\tau_\nu}{\tau_u + \tau_\nu}\, \frac{C}{8}\big[4m - 1\big],$$

which is positive if and only if (41) holds. Then h_λ is strictly increasing on $(0, \bar{b}]$ and exceeds γ at $\bar{b}$, so it equals γ exactly once. The threshold in (41) is below $\frac{1}{4}$. □

B.3 Proof of Proposition 3

The proof follows that of Proposition 4 in Manzano and Vives (2011): f_λ is strictly increasing in λ, so at a regular equilibrium the sign of $\frac{d\beta_u}{d\lambda}$ is that of $1 - f'_\lambda(\beta_u)$. Under $8\gamma^2 > \alpha\tau_\epsilon\tau_\omega$, $f'_\lambda(\beta_u) < 1$ at the unique equilibrium for every adoption rate (Appendix B.1).

(i) At a fixed β_u, a unit increase in λ moves a mass $1-\alpha$ of investors from the group without AI to the AI users. By (56),

$$\frac{\partial f_\lambda}{\partial \lambda} = \frac{1-\alpha}{\gamma}\left[\frac{\tau_\nu + \tau_\xi}{\tau_u + \tau_\nu + \tau_\xi}\left(\tau_p + \tau_2^A\right) - \frac{\tau_\nu}{\tau_u + \tau_\nu}\left(\tau_p + \tau_2\right)\right] > 0,$$

since $\frac{\tau_\nu+\tau_\xi}{\tau_u+\tau_\nu+\tau_\xi} > \frac{\tau_\nu}{\tau_u+\tau_\nu}$ and $\tau_p + \tau_2^A > \tau_p + \tau_2$. By the implicit function theorem applied to $\beta_u = f_\lambda(\beta_u)$,

$$\frac{d\beta_u}{d\lambda} = \frac{\partial f_\lambda/\partial\lambda}{1 - f'_\lambda(\beta_u)}, \tag{63}$$

which is positive at a stable equilibrium and negative at an unstable one, and $\frac{d\beta_u^{-1}}{d\lambda} = -\beta_u^{-2}\frac{d\beta_u}{d\lambda}$ has the opposite sign. By (16), τ_p rises with β_u and does not depend on λ otherwise.

(ii) By (53), $A_v = 1 - \frac{\tau_v}{\tau_v+\alpha\tau_\epsilon+\tau_p+\tau_2+(1-\alpha)\lambda(\tau_2^A-\tau_2)}$, so a change in the market's aggregate signal precision $\alpha\tau_\epsilon + \tau_p + \tau_2 + (1-\alpha)\lambda(\tau_2^A - \tau_2)$ changes A_v by $\frac{(1-A_v)^2}{\tau_v}$ times that change.

Adoption changes the aggregate signal precision directly and through β_u:

$$\frac{dA_v}{d\lambda} = \frac{(1-A_v)^2}{\tau_v}\Bigg\{ \underbrace{(1-\alpha)\left(\tau_2^A - \tau_2\right)}_{\text{composition}} + \underbrace{\left[\left(1-(1-\alpha)\lambda\right)\frac{\partial(\tau_p+\tau_2)}{\partial\beta_u} + (1-\alpha)\lambda\,\frac{\partial(\tau_p+\tau_2^A)}{\partial\beta_u}\right]\frac{d\beta_u}{d\lambda}}_{\text{informativeness}}\Bigg\}. \quad (64)$$

At a stable equilibrium both terms are positive by (58) and (63), and $A_v < 1$ by (53).

(iii) follows from $A_\omega = \frac{\gamma A_v}{\alpha\tau_\epsilon}$. Since $A_u = A_v\beta_u^{-1}$, the price impact of the endowment shock falls, $\frac{dA_u}{d\lambda} < 0$, if and only if $\frac{d\ln\beta_u}{d\lambda} > \frac{d\ln A_v}{d\lambda}$, which is not implied by (i) and (ii) in general.

(iv) Write D_I for the derivative with respect to the mass of informed investors that holds the mass of AI users $m = (1-\alpha)\lambda$ fixed, $D_I = \frac{d}{d\alpha} + \frac{\lambda}{1-\alpha}\frac{d}{d\lambda}$; it turns a unit mass of retail investors without AI into informed investors and raises $\beta_\omega = \frac{\alpha\tau_\epsilon}{\gamma}$ by $\frac{\tau_\epsilon}{\gamma}$. At a fixed β_u, by (56) and (58),

$$D_I f_\lambda = \frac{1}{\gamma}\left[\tau_\epsilon + \frac{\tau_\epsilon}{\gamma}\Big((1-m)\theta_U\frac{\partial P_U}{\partial\beta_\omega} + m\theta_A\frac{\partial P_A}{\partial\beta_\omega}\Big)\right] > 0,$$

and $\frac{\partial f_\lambda}{\partial\gamma} < 0$, because $\frac{1}{\gamma}$ and, through β_ω, P_U and P_A fall with γ. By the implicit function theorem, $D_I\beta_u = \frac{D_I f_\lambda}{1-f'_\lambda(\beta_u)}$ and $\frac{d\beta_u}{d\gamma} = \frac{\partial f_\lambda/\partial\gamma}{1-f'_\lambda(\beta_u)}$, so at a stable equilibrium β_u rises with the mass of informed investors and falls with γ. Since $\tau_p = \left[\frac{\beta_u^{-2}}{\tau_u} + \frac{\gamma^2}{\alpha^2\tau_\epsilon^2\tau_\omega}\right]^{-1}$ rises with β_u and with α and falls with γ, the claim follows. □

Nonfundamental variance and pricing error. The price variance due to the supply shocks is $\frac{A_u^2}{\tau_u} + \frac{A_\omega^2}{\tau_\omega} = \frac{A_v^2}{\tau_p}$, and the share of noise trading in it is $\frac{\tau_p}{\beta_\omega^2\tau_\omega}$, which rises with adoption. Since $v - p = (1-A_v)v - A_v\zeta_p$,

$$\mathrm{Var}(v-p) = \frac{(1-A_v)^2}{\tau_v} + \frac{A_v^2}{\tau_p} = \frac{\tau_v + K^2/\tau_p}{(\tau_v+K)^2}.$$

Along any smooth change of parameters, the pricing error falls if and only if

$$d\ln\tau_p > c\,d\ln K, \qquad c \equiv \frac{2\tau_v(K-\tau_p)}{K(\tau_v+K)} \in (0,2),$$

where $c > 0$ because $K > \tau_p$ and $c < 2$ because $K^2 + \tau_v \tau_p > 0$. The pricing error therefore falls with adoption whenever informativeness grows faster than a fraction c of the market's average precision.

B.4 Values of Information

Derivation of (11). Conditional on $(\mathcal{I}_i, p)$, an investor whose posterior is $\mathcal{N}(\mu_i, \tau_i^{-1})$ and who buys (15) attains the certainty equivalent

$$u_i p + \frac{\tau_i}{2\gamma}(\mu_i - p)^2, \tag{65}$$

that is, conditional expected utility $-\exp\bigl(-\gamma u_i p - \frac{1}{2}\tau_i(\mu_i - p)^2\bigr)$. Let $\tau_i \in \{\tau_A, \tau_I\}$ be the posterior precision with the additional signal. Conditional on (p, u_i), $\mu_i - p$ is normal with mean $\mathbb{E}[v \mid p, u_i] - p$ and variance $\tau_U^{-1} - \tau_i^{-1}$. For $X \sim \mathcal{N}(m, s^2)$,

$$\mathbb{E}\bigl[\exp(-\tfrac{1}{2}\tau_i X^2)\bigr] = (1 + \tau_i s^2)^{-1/2} \exp\Bigl(-\frac{\tau_i m^2}{2(1 + \tau_i s^2)}\Bigr),$$

and here $1 + \tau_i s^2 = \frac{\tau_i}{\tau_U}$. The exponent therefore equals $-\frac{1}{2}\tau_U m^2$, the exponent without the signal. Because $u_i p$ is known given (p, u_i), expected utility with the additional signal is $\bigl(\frac{\tau_U}{\tau_i}\bigr)^{1/2}$ times expected utility without it, for every realization of (p, u_i), as in Corollary 5 of Manzano and Vives (2011). A certainty-equivalent cost c multiplies expected utility by $e^{\gamma c}$, so the investor is indifferent at $c = \frac{1}{2\gamma} \ln \frac{\tau_i}{\tau_U}$. Integrating over (p, u_i) gives the same ratio ex ante whenever ex-ante expected utility is finite. □

By (19) and (26), with $\frac{\beta_\omega^{-2}}{\tau_\omega} = \frac{\gamma^2}{\alpha^2 \tau_\epsilon^2 \tau_\omega}$,

$$\begin{aligned} G_A &= \frac{1}{2\gamma} \ln \frac{\tau_v + \left[\beta_u^{-2}/(\tau_u + \tau_\nu + \tau_\xi) + \gamma^2/(\alpha^2 \tau_\epsilon^2 \tau_\omega)\right]^{-1}}{\tau_v + \left[\beta_u^{-2}/(\tau_u + \tau_\nu) + \gamma^2/(\alpha^2 \tau_\epsilon^2 \tau_\omega)\right]^{-1}}, \\ G_I &= \frac{1}{2\gamma} \ln \left(1 + \frac{\tau_\epsilon}{\tau_v + \left[\beta_u^{-2}/(\tau_u + \tau_\nu) + \gamma^2/(\alpha^2 \tau_\epsilon^2 \tau_\omega)\right]^{-1}}\right). \end{aligned} \tag{66}$$

Other investors' choices affect the values only through the two price ratios β_u and $\beta_\omega = \frac{\alpha \tau_\epsilon}{\gamma}$.

Lemma 1 (Price informativeness and the value of information)**.** *Holding the other price ratio fixed:*

(i) The value of the payoff signal falls with both price ratios:

$$\frac{\partial G_I}{\partial \beta_u} = -\frac{\beta_u^{-3}}{\gamma}\,\frac{\tau_\epsilon(\tau_p+\tau_2)^2}{(\tau_u+\tau_\nu)\tau_U\tau_I} < 0, \qquad \frac{\partial G_I}{\partial \beta_\omega} = -\frac{\beta_\omega^{-3}}{\gamma\tau_\omega}\,\frac{\tau_\epsilon(\tau_p+\tau_2)^2}{\tau_U\tau_I} < 0.$$

(ii) The value of the AI signal changes with β_u by

$$\frac{\partial G_A}{\partial \beta_u} = \frac{\beta_u^{-3}}{\gamma}\left[\frac{(\tau_p+\tau_2^A)^2}{(\tau_u+\tau_\nu+\tau_\xi)\tau_A} - \frac{(\tau_p+\tau_2)^2}{(\tau_u+\tau_\nu)\tau_U}\right]. \tag{67}$$

It is positive if and only if $\tau_A\tau_U < \tau_v(\tau_v+\beta_\omega^2\tau_\omega)$, which is (47).

(iii) The value of the AI signal rises with β_ω:

$$\frac{\partial G_A}{\partial \beta_\omega} = \frac{\beta_\omega^{-3}}{\gamma\tau_\omega}\left[\frac{(\tau_p+\tau_2^A)^2}{\tau_A} - \frac{(\tau_p+\tau_2)^2}{\tau_U}\right] > 0.$$

Proof. The derivative formulas follow directly from (11) and (58). Part (i) uses $\partial G_I/\partial\tau_U = -\tau_\epsilon/(2\gamma\tau_U\tau_I)$. For part (iii), put $P_U = \tau_p+\tau_2$ and $P_A = \tau_p+\tau_2^A$. Because $P_A > P_U$ and $P \mapsto P^2/(\tau_v+P)$ is increasing, the displayed derivative is positive.

For part (ii), let $C = \beta_\omega^2\tau_\omega$ and define

$$\phi(P) = \frac{P(1-P/C)}{\tau_v+P}.$$

Writing $T_U = \tau_u+\tau_\nu$ and $T_A = \tau_u+\tau_\nu+\tau_\xi$, the identity $\beta_u^{-2}P_k/T_k = 1-P_k/C$ for $k\in\{U,A\}$ makes the sign of $\partial G_A/\partial\beta_u$ the sign of $\phi(P_A)-\phi(P_U)$. A direct subtraction gives

$$\phi(P_A)-\phi(P_U) = \frac{(P_A-P_U)[\tau_v C - \tau_v(P_A+P_U) - P_AP_U]}{C(\tau_v+P_A)(\tau_v+P_U)}.$$

As $P_A > P_U$, this difference is positive exactly when $(\tau_v+P_A)(\tau_v+P_U) < \tau_v(\tau_v+C)$, or equivalently $\tau_A\tau_U < \tau_v(\tau_v+C)$.

□

B.5 Proof of Proposition 4

The argument is that of Proposition 6 in Manzano and Vives (2011): by (11), the value of a signal depends on others' acquisition only through the price ratios, so its derivative is the derivative of the value with respect to the price ratio, from Lemma 1, times the comparative static of the trading equilibrium, whose sign is that of $1 - f'_\lambda(\beta_u)$ by the implicit function theorem. Parts (i) and (ii) concern any regular trading equilibrium, $f'_\lambda(\beta_u) \neq 1$; parts (iii) and (iv) assume a stable one, $f'_\lambda(\beta_u) < 1$, which under $8\gamma^2 > \alpha\tau_\epsilon\tau_\omega$ is the unique equilibrium. D_I is the derivative with respect to the mass of informed investors at a fixed mass of AI users, as in Appendix B.3.

Effect of others' acquisition on the price. Adoption raises β_u by (63) and leaves β_ω unchanged. Turning investors without AI into informed investors raises β_ω by $D_I\beta_\omega = \frac{\tau_\epsilon}{\gamma}$. At a fixed β_u, it raises $\alpha\tau_\epsilon$ in (56) by τ_ϵ, and it raises $\tau_p + \tau_2$ and $\tau_p + \tau_2^A$ through β_ω, by (58):

$$\frac{\partial(\tau_p + \tau_2)}{\partial\beta_\omega}\,\frac{\tau_\epsilon}{\gamma} = \frac{2\gamma^2(\tau_p + \tau_2)^2}{\alpha^3\tau_\epsilon^2\tau_\omega},$$

and similarly for AI users. The masses of investors with and without AI are unchanged. By the implicit function theorem,

$$D_I\beta_u = \frac{1}{\gamma\big(1 - f'_\lambda(\beta_u)\big)}\Bigg[\tau_\epsilon + \frac{2\gamma^2}{\alpha^3\tau_\epsilon^2\tau_\omega}\left(\big(1-(1-\alpha)\lambda\big)\frac{\tau_\nu(\tau_p+\tau_2)^2}{\tau_u+\tau_\nu} + (1-\alpha)\lambda\,\frac{(\tau_\nu+\tau_\xi)(\tau_p+\tau_2^A)^2}{\tau_u+\tau_\nu+\tau_\xi}\right)\Bigg] > 0. \quad (68)$$

The value of the payoff signal (part iii). By Lemma 1(i),

$$\frac{dG_I}{d\lambda} = \frac{\partial G_I}{\partial\beta_u}\,\frac{d\beta_u}{d\lambda} < 0, \qquad D_I G_I = \frac{\partial G_I}{\partial\beta_u}\,D_I\beta_u + \frac{\partial G_I}{\partial\beta_\omega}\,\frac{\tau_\epsilon}{\gamma} < 0.$$

The value of the AI signal (part i). By the chain rule and (63),

$$\frac{dG_A}{d\lambda} = \frac{\partial G_A}{\partial\beta_u}\,\frac{d\beta_u}{d\lambda} = \frac{\partial G_A}{\partial\beta_u}\,\frac{\partial f_\lambda/\partial\lambda}{1 - f'_\lambda(\beta_u)},$$

with $\frac{\partial f_\lambda}{\partial \lambda} > 0$, so at a stable equilibrium the sign is that of $\frac{\partial G_A}{\partial \beta_u}$ and at an unstable one it is reversed. Lemma 1(ii) gives (47) as an exact characterization. For (46), write $x = \beta_u^{-2}$, $T = \tau_u + \tau_\nu$, and $S = \tau_u + \tau_\nu + \tau_\xi$, so that by (19) and (26) $P_U = \frac{CT}{Cx+T}$ and $P_A = \frac{CS}{Cx+S}$. Substituting into $\tau_A \tau_U = \tau_v(\tau_v + C)$ and clearing denominators, the terms in τ_v^2 and in $\tau_v C x(S+T)$ cancel, leaving $\tau_v C^2 x^2 = TS(\tau_v + C)$, so the knife edge is $x^* = \frac{1}{C}\sqrt{TS\big(1 + \frac{C}{\tau_v}\big)}$, that is, $\beta_u^{-1} = b^*$. Since $\tau_A \tau_U$ decreases in β_u^{-1}, (47) holds if and only if $\beta_u^{-1} > b^*$; no bounding inequality is used, so (47) and (46) are the same condition.

The bound on the price ratio and the global condition (part ii). Write $\kappa \equiv \frac{\alpha\tau_\epsilon\tau_\omega}{\gamma^2} = \frac{C}{\alpha\tau_\epsilon}$. In (33), each supply term is $\frac{C}{\gamma} w_k \Psi_k \frac{P_k}{C}$ with $w_U = 1 - (1-\alpha)\lambda$, $w_A = (1-\alpha)\lambda$, $\Psi_k < 1$, and $\frac{P_k}{C} < 1$ at every finite β_u, so

$$f_\lambda(\beta) < \beta_\omega + \frac{C}{\gamma}(w_U \Psi_U + w_A \Psi_A) \le \beta_\omega + \frac{C}{\gamma} = \bar{\beta}$$

for every β, and every fixed point satisfies $\beta_u < \bar{\beta}$. (The sharper bound with the weights kept, $\bar{\beta}_\lambda = \beta_\omega[1 + \kappa(w_U \Psi_U + w_A \Psi_A)]$, is increasing in λ, so its value at $\lambda = 1$ covers every adoption rate.) Then $\beta_u^{-1} > \bar{\beta}^{-1} = \frac{\gamma}{\alpha\tau_\epsilon + C}$, and $\bar{\beta}^{-1} > b^*$ is equivalent to

$$\frac{\gamma^2 C}{(\alpha\tau_\epsilon + C)^2} > \sqrt{TS\Big(1 + \frac{C}{\tau_v}\Big)};$$

since $\frac{\gamma^2 C}{(\alpha\tau_\epsilon)^2} = \tau_\omega$ and $\alpha\tau_\epsilon + C = \alpha\tau_\epsilon(1+\kappa)$, this is (50), and $\bar{\beta} = \beta_\omega(1+\kappa)$ is (48).

The second bound uses the market-clearing condition (57) in $b = \beta_u^{-1}$, with $y_U = \frac{T}{C}$ and $y_A = \frac{S}{C}$. For $x, y > 0$, $\frac{xb}{b^2 + y} \le \frac{x}{2\sqrt{y}}$, with equality at $b^2 = y$; this is the peak of the hump whose slope the proof of Proposition 1(iv) bounds. Hence

$$\gamma = h_\lambda(b) \le \alpha\tau_\epsilon b + \frac{\sqrt{C}}{2}\left[w_U \frac{\tau_\nu}{\sqrt{T}} + w_A \frac{\tau_\nu + \tau_\xi}{\sqrt{S}}\right],$$

and since $\frac{\sqrt{C}}{2\alpha\tau_\epsilon} = \frac{\gamma}{\alpha\tau_\epsilon} \frac{\alpha\tau_\epsilon\sqrt{\tau_\omega}}{2\gamma^2}$, every equilibrium satisfies

$$b \ge \frac{\gamma}{\alpha\tau_\epsilon}\Big(1 - \frac{\chi_\lambda}{2}\Big),$$

which is the stated bound on β_u when $\chi_\lambda < 2$; (36) is $\chi_\lambda < \frac{8}{3\sqrt{3}} < 2$. The bracket in (49) increases in λ, because $\frac{\tau_\nu+\tau_\xi}{\sqrt{S}} > \frac{\tau_\nu}{\sqrt{T}}$, so $\chi_\lambda \leq \chi_1$. By the same algebra as for $\bar{\beta}$, $\frac{\gamma}{\alpha\tau_\epsilon}\left(1-\frac{\chi_1}{2}\right) > b^*$ is (50) with $\left(1-\frac{\chi_1}{2}\right)^{-2}$ in place of $(1+\kappa)^2$.

Under either condition, (46) holds at every fixed point of f_λ for every λ, and part (i) gives the signs at stable and unstable equilibria. For nonemptiness, fix κ and set $\gamma^2 = \frac{\alpha\tau_\epsilon\tau_\omega}{\kappa}$, so that $C = \alpha\tau_\epsilon\kappa$ is fixed; the right-hand side of (50) is then a constant and the left-hand side is proportional to τ_ω, so the condition holds for all τ_ω above the stated value. Since both sides are continuous in the parameters, the set is open, and $\kappa < 8$ can be imposed throughout.

Cross effect of informed investors (part iv). By the chain rule,

$$D_I G_A = \frac{\partial G_A}{\partial \beta_u} D_I \beta_u + \frac{\partial G_A}{\partial \beta_\omega} \frac{\tau_\epsilon}{\gamma}.$$

The second term is positive by Lemma 1(iii). Whenever adoption is a strategic complement, $\frac{\partial G_A}{\partial \beta_u} > 0$, and with (68) the first term is positive as well. □

A tighter sufficient condition at the least informative equilibrium. Let $s_\lambda \equiv \tau_\nu + (1-\alpha)\lambda\tau_\xi$ be the average precision of investors' supply signals and suppose that $\gamma^2 \geq 4\alpha\tau_\epsilon s_\lambda$. At the least informative trading equilibrium, which is stable whenever it is regular, the relative price impact of the endowment shock is bounded on both sides by that of noise trading,

$$\beta_\omega^{-1}\left(1 - \frac{2\alpha\tau_\epsilon s_\lambda}{\gamma^2}\right) \leq \beta_u^{-1} < \beta_\omega^{-1} = \frac{\gamma}{\alpha\tau_\epsilon}, \tag{69}$$

so that (46) holds, and adoption is a strategic complement at that equilibrium, whenever

$$\sqrt{(\tau_u+\tau_\nu)(\tau_u+\tau_\nu+\tau_\xi)}\sqrt{1+\frac{\alpha^2\tau_\epsilon^2\tau_\omega}{\gamma^2\tau_v}} \;<\; \tau_\omega\left(1-\frac{2\alpha\tau_\epsilon s_\lambda}{\gamma^2}\right)^2. \tag{70}$$

The lower bound in (69) is the smaller fixed point of the economy without noise trading (Remark 1); the upper bound is Proposition 1(iii). Condition (70) becomes harder to satisfy as adoption raises s_λ.

Derivation. (i) By (19) and (26), the precision of price information of an investor whose

supply signal has precision τ_k satisfies $P_k \le (\tau_u + \tau_k)\beta_u^2$, so with $\Psi_k = \frac{\tau_k}{\tau_u+\tau_k}$ the aggregate best response (56) satisfies, for every β,

$$f_\lambda(\beta) \le \frac{\alpha\tau_\epsilon + \beta^2 \sum_k w_k\tau_k}{\gamma} = \frac{\alpha\tau_\epsilon + s_\lambda\beta^2}{\gamma} \equiv g(\beta).$$

The function g is the aggregate best response of the economy without noise trading (Remark 1). Under $\gamma^2 \ge 4\alpha\tau_\epsilon s_\lambda$ it has two fixed points, the smaller of which is

$$\underline{\beta}_\lambda = \frac{\gamma - \sqrt{\gamma^2 - 4\alpha\tau_\epsilon s_\lambda}}{2s_\lambda}.$$

Since $f_\lambda(0) = \frac{\alpha\tau_\epsilon}{\gamma} > 0$ and $f_\lambda(\underline{\beta}_\lambda) \le g(\underline{\beta}_\lambda) = \underline{\beta}_\lambda$, f_λ has a fixed point in $(0, \underline{\beta}_\lambda]$, so the smallest fixed point $\beta_u^{\min}$ satisfies $\beta_u^{\min} \le \underline{\beta}_\lambda$. At the smallest fixed point f_λ crosses the diagonal from above, so $f'_\lambda \le 1$ there, with strict inequality if the equilibrium is regular, which is the stability condition. Rationalizing,

$$\underline{\beta}_\lambda^{-1} = \frac{\gamma + \sqrt{\gamma^2 - 4\alpha\tau_\epsilon s_\lambda}}{2\alpha\tau_\epsilon},$$

and $\sqrt{1-x} \ge 1 - x$ for $x \in [0,1]$ gives $\underline{\beta}_\lambda^{-1} \ge \frac{\gamma}{\alpha\tau_\epsilon} - \frac{2s_\lambda}{\gamma}$, which with $(\beta_u^{\min})^{-1} \ge \underline{\beta}_\lambda^{-1}$ is the lower bound in (69); the upper bound is Proposition 1(iii). Under $8\gamma^2 > \alpha\tau_\epsilon\tau_\omega$ the fixed point is unique by Proposition 1(iv).

(ii) The knife edge (46) reads $\beta_u^{-2} > \frac{1}{C}\sqrt{TS\big(1 + \frac{C}{\tau_v}\big)}$, and the lower bound in (69) implies it whenever

$$\frac{\gamma^2}{\alpha^2\tau_\epsilon^2}\Big(1 - \frac{2\alpha\tau_\epsilon s_\lambda}{\gamma^2}\Big)^2 > \frac{1}{C}\sqrt{TS\Big(1 + \frac{C}{\tau_v}\Big)};$$

since $\frac{C\gamma^2}{\alpha^2\tau_\epsilon^2} = \tau_\omega$, this is (70).

Exact threshold in the precision of the AI signal. At $\lambda = 0$, $\beta_u(0)$ does not depend on τ_ξ, and (46) is equivalent to

$$\tau_\xi < \frac{\beta_u(0)^{-4}C^2}{(\tau_u + \tau_\nu)\big(1 + \frac{C}{\tau_v}\big)} - (\tau_u + \tau_\nu),$$

where $\beta_u(0)^{-1}$ is the unique positive root of the cubic (62): without adoption, the AI signal is a complement if and only if it is not too precise.

B.6 Proof of Proposition 5

(i) The proof follows that of Proposition 6 in Manzano and Vives (2011). Without AI, $\lambda = 0$ and $D_I = \frac{d}{d\alpha}$. By (66), the mass of informed investors affects G_I only through the price ratios, so

$$\frac{dG_I}{d\alpha} = \frac{\partial G_I}{\partial \beta_u}\frac{d\beta_u}{d\alpha} + \frac{\partial G_I}{\partial \beta_\omega}\frac{\tau_\epsilon}{\gamma},$$

where both partial derivatives are negative by Lemma 1(i) and $\frac{d\beta_\omega}{d\alpha} = \frac{\tau_\epsilon}{\gamma} > 0$. By (68), $\frac{d\beta_u}{d\alpha}$ has the sign of $1 - f_0'(\beta_u)$. At a stable equilibrium both terms are negative, so $\frac{dG_I}{d\alpha} < 0$. At an unstable equilibrium, $\frac{d\beta_u}{d\alpha} < 0$ and the first term is positive, while the second remains negative.

(ii) If $8\gamma^2 > \frac{\tau_\epsilon \tau_\omega \tau_\nu}{\tau_u + \tau_\nu}$, then $8\gamma^2 > \frac{\alpha \tau_\epsilon \tau_\omega \tau_\nu}{\tau_u + \tau_\nu}$ for every $\alpha \leq 1$, which is the strict version of (37) at $\lambda = 0$. The trading equilibrium is then unique and stable for every α, and the value of the payoff signal $G_I(\alpha)$ is continuous and strictly decreasing. Let F be the distribution of acquisition costs in the population. A mass α of informed investors is an equilibrium if investors with costs below $G_I(\alpha)$ acquire and those with costs above do not, that is, since the masses of investors with costs strictly below g and with costs at most g are $F(g^-)$ and $F(g)$, $F(G_I(\alpha)^-) \leq \alpha \leq F(G_I(\alpha))$. If $\alpha' > \alpha$ were both equilibria, then $G_I(\alpha') < G_I(\alpha)$ and $\alpha' \leq F(G_I(\alpha')) \leq F(G_I(\alpha)^-) \leq \alpha$, a contradiction. Since the correspondence $\alpha \mapsto [F(G_I(\alpha)^-), F(G_I(\alpha))]$ is nonincreasing and has a closed graph, it crosses the diagonal, so the equilibrium exists and is unique. □

B.7 Proof of Proposition 6

Under the uniform strict uniqueness condition, the scalar equation (57) has a strictly positive derivative in $b = \beta_u^{-1}$. The analytic implicit function theorem therefore makes $b(\lambda)$, and hence $G_A(\lambda)$, real analytic on a neighborhood of $[0, 1]$. By Proposition 4(i), the strict threshold at $\lambda = 0$ implies $G_A'(0) > 0$, so $M \equiv \max_{[0,1]} G_A > G_A(0)$.

Fix $G_A(0) < c < M$ and choose a maximizer $\lambda_m > 0$. Since $G_A(0) < c$, zero adoption is a stable equilibrium. The analytic function $G_A - c$ is not identically zero; it has only finitely many zeros on $[0, 1]$. It starts negative and is positive at λ_m, so at least one of its zeros in $(0, \lambda_m)$ is a sign-changing crossing from below. Choose such a zero as λ_1. At λ_1, adoption

just below the equilibrium is unattractive and adoption just above it is attractive, so the equilibrium is unstable.

After λ_1, either $G_A - c$ crosses from positive to negative, in which case any such downward crossing $\lambda_2 \in (\lambda_1, 1)$ is a stable equilibrium, or it never crosses downward. In the latter case it is positive just below and at $\lambda = 1$ (or zero at the endpoint), so full adoption $\lambda_2 = 1$ is a stable equilibrium. Thus zero, λ_1, and λ_2 are distinct adoption equilibria, with the claimed stability properties. □