



Journal of Information Economics

Homepage: <https://www.anserpress.org/journal/jie>



It is All About Information: Six Common Fallacies in Financial Economics

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ABSTRACT

Based on the results of a simple Agent Based Model (ABM) six common and widely affirmed statements in financial economics are discussed: (1) The better an investor is informed, the higher his performance is expected to be, (2) There is a well-defined state of art how to make sound financial decisions, (3) High standards of public information create private as well as public value, (4) Highly skilled financial analysts usually decide better than their lousy colleagues, (5) The market loses informational efficiency if traders abstain from information, (6) To use Bayes' updating rule means to make rational financial decisions. Financial markets are complex adaptive systems, in order to understand them, the interaction of autonomous agents has to be brought into the focus. As the ABM methodology allows to do this better than neoclassical methods, this simple technique is adopted and allows to evidence that all these beliefs, even if they may be deeply rooted in the profession, are probably false.

KEYWORDS

Financial Analysis; Information in Financial Markets; Information-Based Investment Strategy; Market Efficiency; Public Information in Investment Decisions

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ISSN 2972-3671

doi: 10.58567/jie02040002

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Received 28 July 2024; Accepted 11 November 2024; Available online 10 January 2025; Version of Record 15 December 2024

1. Introduction

Modern financial economics have been developed on two methodologically distinct avenues. The one grounds on a normative decision model of Markowitz. In his seminal paper, he accentuated to consider the second and not the first stage of selecting a portfolio, i.e. “the formation of the relevant beliefs on the basis of observation” (Markowitz, 1952). His scholar Sharpe asked in 1964 what happens in an economy if investors act as portfolio theory suggests they should. Based upon the Markowitz model and its assumptions he created the core model of positive capital market theory, the CAPM (similar to *Treynor*, *Lintner*, and *Mossin*). He derived his model from homogeneous beliefs as an additional assumption in the true deductive logic of neoclassical economics. But both, the normative as well as the positive model, depend upon the first stage, both require a diligent appraisal of information by the investors.

The other avenue is rather grounded on empirical observations. Even if a theoretical root dates back to the beginning of the 20th century (Bachelier, 1900), this has not been acknowledged for more than half a century. In the 1930-50ies, several researchers found random patterns in stock prices, but, for a long time, the academic community regarded these phenomena, although they got more and more empirically confirmed, as confusing. With his indicative article “Proof That Properly Anticipated Prices Fluctuate Randomly” Samuelson (1965) took up the ideas of Bachelier and gave a first theoretical foundation to the random patterns in stock prices found in numerous empirical studies. Fama’s essay “Efficient Capital Markets”, probably the most cited paper in financial economics ever, was mainly concerned with these empirical studies of stock price behaviour and how to classify them. But the paper became famous as it coined the basic concept of the Efficient Markets Hypothesis (EMH), saying that a capital market is called informationally efficient, if “prices always ‘fully reflect’ all available information” (Fama, 1970). The fact that the EMH has, despite some theoretical flashlights, mainly an empirical origin, was more a strength than a weakness: practitioners could not so easily denunciate it as a pure theoretical chimera.

Both avenues, the mainly theoretical CAPM, and the mainly empirical EMH, constitute the core of academic finance and opened the way to very fruitful further developments like derivatives pricing and much more. But even if both avenues are strongly related to the topos ‘information’, basic findings of information economics have scarcely attracted interest in financial economics. The information issue has been widely discussed following the seminal articles of Grossman (1976) and Grossman and Stiglitz (1980) and the price discovery discussion initiated by Easley and O’Hara (2004); in both cases, the main interest was rather on the information content of the observed prices, than on the problem how these prices are generated in a market context and what is the consequence of such a market interaction. There has been no serious attempt to consider the central rule of Austrian economics, that “economics must show how a solution is produced by the interactions of people each of whom possesses only partial knowledge” (Hayek, 1945). Interaction with people being differently informed takes place in a complex, highly interdependent, and adaptive system. If in our models we do not seriously address complexity, we will not get a sound understanding of how financial markets work. To consider the complexity of financial markets, at least we should take into account that.

- an equilibrium is not a given attractor, but it is path-dependent, not stable, always adapting to new circumstances and thus opening the way to new unstable equilibria (*adaptive systems*)
- market prices are the outcome of individual decision-makers who decide as it seems best for them (*methodological individualism; whatever we observe in the social world is the result of individual decisions*)
- any trader has an incentive to do what he is supposed to do (*humans act only if they assume that the action makes them better off*)
- there are no foolish investors like noise traders, who do worse than they could (*even if traders are not expected to be perfectly rational, their decisions at least have to be purposeful*)

- any strategy chosen by an investor has to be the best answer to the strategies of the others (*this is the case if the system moves towards a Nash equilibrium*).

2. Model Analysis

An analytical model (in the tradition of neoclassic economics) that satisfies all these requirements will be extremely difficult to establish. Therefore, we believe that it will not come up in the next decades; at least it will not come up without multiple heroic assumptions. We, neither, can present such a model and we do not even dare to contour it; it is far beyond our intellectual capacities. However, simulations, especially agent-based modeling (ABM) offer a powerful alternative to closed-form models. ABM is, first of all, modeling interaction; it allows us to understand interaction in an economic setting just by observing what happens if people (agents) act in a well-defined way. As in complex systems the system's behavior is not linearly related to the behavior of its components, we just have to model the behavior of the agents and to interpret thoroughly the emerging system properties. The ABM used in this paper is extremely simple (Schredelseker, 2014), but it considers interaction and allows us to put seriously into question some of the central beliefs in financial economics. It can be easily reproduced in a common Excel-file.

The model. In a closed one-period market there are ten traders T_n ($T_0 \dots T_9$) trading a security; its value V is the sum of ten binary signals $S_j(0,1)$. Thus, traders know that V is binomially distributed in the interval $0 \dots 10$ with a mean of 5. To capture information asymmetry, we let any T_n be aware of the first n signals, i.e., his information level will be IL_n . Hence information is assumed to be cumulative: level IL_n implies any $IL_{<n}$. The alternative would be an independent information structure sampling with replacement, but we think that this is far away from real markets: we believe that what a medium-informed investor knows, is anyway known to the better informed. Based upon their information, in a first step, traders follow the common rules of financial analysis, i.e., they make the best possible estimation of V : to the known n signals the expected value of the unknown is added. T_n 's estimation is thus $E_n(V) = \sum_{j=1}^n S_j + (10-n)/2$. As nobody knows the 10th signal, the intrinsic value V^0 of the security equals $E_9(V) = \sum_{j=1}^9 S_j + 0.5$, the estimation of the best informed T_9 . V , the real value of the security when the 10th signal is revealed, is thus either $V^0+0.5$ or $V^0-0.5$.

In this basic model traders trade just one unit of the security: T_n buys if he perceives the security to be underpriced [$E_n(V) > P$], and sells if he believes it to be overpriced [$E_n(V) < P$]. The market clearing price P is set by a common call-market procedure; as orders are not continuously distributed, sometimes rationing may be necessary to maintain the zero-sum-property of the market. At the end of the period all positions are cleared: buyer's payoff is $V-P$ and seller's is $P-V$. If the security is undervalued ($P < V$) buyers win and sellers lose, if it is overvalued sellers win and buyers lose. All results presented in the sequel are calculated as the arithmetic mean of all $2^{10}=1024$ possible realizations of ten binary signals. Thus, in contrast to Monte-Carlo simulations with the utilization of random numbers, the results of the presented ABM are free of any fuzziness and can exactly be reproduced. As the simulated market with ten traders is very thin, it will be far away from being informationally efficient: in some cases, it may happen that $P=V$, but usually we will see over- or underpricings, results with $P \neq V$. This is welcome, as we want to study information asymmetry in markets being not perfectly efficient. In the limited case of a strong-form-efficient market with $P=V$, reasoning on information is virtually useless. In that case, the theoretical challenge is different: it has to be explained not how, but why investors should deal with information.

3. Important assertions

In the sequel, we have a closer look at some widely spread convictions, if financial markets are supposed to be informationally somewhat inefficient.

3.1. The better an investor is informed, the higher his performance is expected to be

If we disregard counterfactual information, getting more information should never make a decision-maker worse off. In decisions against nature, there is no doubt: new information has either zero value and we disregard it or it enhances our knowledge and allows us to make better decisions. In games or markets this is not necessarily the case as additional information (whether given to some or all agents) can change the whole game (Hule and Lawrenz, 2008). If in a financial market, a trader gets better informed, this will have two consequences: On the one hand, more information makes him make less misspecifications (his estimations become more precise), on the other hand, more information makes him join the herd of all those who also have this or a similar type of information; doing so he will make decisions being more synchronized with the decisions of others. The first effect improves, and the second hurts his investment performance. Therefore, the relationship between information level and expected performance may be not linear, as usually is supposed in common textbooks. If it is non-linear, it may be the case that up to a certain level a trader is worse off with additional information, thereafter he will become better off. This is what has been evidenced in the basic ABM.

Table 1. Information level and performance.

Trader:	T ₀	T ₁	T ₂	T ₃	T ₄	T ₅	T ₆	T ₇	T ₈	T ₉
EP (expected payoff):	-0.34	-0.38	-0.40	-0.37	-0.31	0.03	0.22	0.39	0.51	0.64

Table 1 reports the expected payoffs (EP) for ten traders if they all follow the fundamentalist maxim to make the best estimate of the firm's true value based on their information. Partly it confirms usual expectations: well informed traders (T₅...T₉) win and badly informed traders (T₀...T₄) lose; naturally the sum of the payoffs has to be zero. However, inconsistent with common wisdom but following the previous logic is, that the biggest loser is not the one with the lowest information. Although they are better informed, traders T₁, T₂, and T₃ perform worse than the uninformed trader T₀, even if their estimations E(V) are undoubtedly more precise. This result, even if it seems somewhat struggling, can easily be explained. Let us have a look at three typical sequences of nine binary signals; as nobody knows the 10th signal it is disregarded and will be considered with its expected value 0.5.

Basically, there are three types of sequences:

- *quite uniform sequences* (in extremis 111111111 or 000000000). In this case, the clearing price P will be halfway between the true value and the average '5', the estimation of the uninformed. In the first case, the security is underpriced with an intrinsic value of V°=9.5 and a price of P=7.25. Low informed traders underestimate it, whereas well informed acknowledge the underpricing; the first sell and lose, the latter buy and win. In the second case, with V°=0.5, the security is overpriced with 2.75 and low informed traders buy, whereas well informed sell. Good informed traders (T₅..T₉) win and bad informed traders (T₀..T₄) lose; this is perfectly in line with conventional wisdom.

- *oscillating sequences* (in extremis 101010101 or 110011001). In this case, P is near (5.25) or at (5.50) the true value and whether a trader will end up as a winner or as a loser depends on chance, on the position of the last signal. With V=6 buyers win and sellers lose a small amount, with V=5 sellers win and buyers lose a small amount. This result is quite similar to an informationally efficient market: the probability to be a winner or a loser is the same for everybody, it does not depend on his information.

- *mean-reverting sequences* (in extremis 111110000 or 000001111). In the first case, the security will be overpriced with P=6.25: mid-informed traders (T₃,T₄,T₅,T₆,T₇) will overestimate an overpriced security and buy it. In the second case, the market price will be P=3.75: mid-informed traders (T₃,T₄,T₅,T₆,T₇) will underestimate an underpriced security and sell it. In both cases poorly informed traders (T₀,T₁,T₂) know too less to get part of the herd and well informed traders (T₈,T₉) know enough not to be affected by the biased information.

As all possible sequences of ten signals can roughly be assigned to one of these three stylized types, it becomes obvious, that mid-informed traders have no chance to perform systematically better (or even as good) as bad informed or even non-informed traders.

Unfortunately, we do not have a reliable answer to what it means in a real market to be *mid-informed*; this is an empirical question. Nevertheless, some reflections may allow us a tentative approach to an answer. In the basic ABM we considered an artificial market, where the total market volume has been split up into ten deciles: the model provides ten different information levels, in each of them exactly one trader is trading exactly one unit of the security. Real markets, however, usually are characterized by sharp disparities: we have it to do with a huge number of traders investing quite modest amounts of money and very few investors having huge sums under management. The results of the ABM remain the same, if we change the number of traders and their budgetary constraints, as long as each of the cohorts still stands for one decile of the total market. This is e.g. the case when in each of the ten cohorts $j_1 \dots j_{10}$ there are z^{10-j} traders, who trade z^j units each; the higher z the more distinctive is the inequality. If we take $z=5$ and a 1000\$-unit, in the first cohort roughly 1.95m traders are investing 5,000\$ each, in the second cohort 390,625 traders invest 25,000\$ each and so on; in the 10th decile there is just one trader left who has about 9.8tn\$ under management. In such a setting it can be assumed that the IL of a trader is strongly related to the amount he has under management: the more it is, the more he can spend for costly information and the higher his IL will be. This assumption allows us to align the cohorts $j_1 \dots j_{10}$ to the information levels $IL_{0,9}$: the richer a trader is, the higher will be his IL. As still each information level is assigned one decile of the whole market, the results of table 1 apply as before.

If you consider as 'good informed' all traders with an information level IL4 or higher, in the basic ABM (with $z=1$) 60% of the traders belong to that category, but in the case of $z=5$ only 0.16% of the traders are among these *better informed* and 99.84% of the traders can hardly expect to have an advantage from their information activities. We guess that the assumed $z=5$ is rather too low to be a good proxy for real market inequalities. Whatever the empirical distribution of wealth may be, for the large majority of investors seems to be little hope that they can improve their investment performance simply by getting better informed if information is costly.

3.2. *There is a well-defined state of the art how to do sound financial decisions*

Table 1 reports the payoffs under the assumption that all traders follow a fundamentalist decision strategy; they do what theory as well as practice for decades asked them to do. In markets being informationally not efficient it is assumed that investors should estimate expected returns, variances, covariances, risk premia, betas etc. and using these data they should optimize their portfolios. Practitioners-to-be are requested to study the voluminous material of the CFA institute, where mainly financial analysis based upon publicly available information is in the limelight. But even if information gathering is the omnipresent advice, nobody is bound to obey. Already in the 1970ies the financial industry offered facilities for those who wanted to escape from the information trap: John Bogle launched the first public index funds and started an incomparable success story which persists till now in the form of indexed ETFs. A market where all investors follow a fundamentalist strategy is not conceivable. If the market is informationally efficient, gathering information is useless and should be avoided, at least to avoid cost. If the market, however, is not perfectly efficient, there will be systematic winners and systematic losers, for whom it is rational not to consider the information they have. In both cases to switch to a passive strategy as investing in indexed ETFs is a rational move.

This, too, can be confirmed in the ABM, where a 'passive investment strategy' just means to make decisions not based upon information. If a passive trader decides by flipping a coin whether to buy or to sell the security, the probability to get on the winning side is the same as to get to the losing side of the market. Table 2 shows what happens, if, beginning with trader T_0 , more and more traders switch to such a passive strategy. If only T_0 decides to

flip a coin, he is much better off with a payoff -0.10 instead of -0.34: his expected payoff, however, is not zero, because of the thinness of the market, where each trader has a considerable impact on the market price (in an ABM with 20 traders the EP of T_0 , as long as he is the only to decide passively, would be -0.04).

As an ABM has in consideration the whole market and not only isolated optimizers, the expected payoffs of all traders are affected if a trader changes strategy: If T_0 switches to a passive strategy, he as well as T_1 , T_2 , and T_3 are better off, whereas all others are worse off. As in the classical matching-penny-game, the underdog can easily withdraw himself from the loser's position by switching to a random choice.

Table 2. Traders switch to a passive strategy.

Trader:	T_0	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9
EP (no passive trader):	-0.34	-0.38	-0.40	-0.37	-0.31	0.03	0.22	0.39	0.51	0.64
EP (one passive trader):	-0.10	-0.31	-0.36	-0.36	-0.33	-0.11	0.14	0.33	0.48	0.62
EP (two passive traders):	-0.11	-0.11	-0.30	-0.32	-0.32	-0.18	0.04	0.27	0.43	0.58
EP (three passive traders):	-0.12	-0.12	-0.12	-0.26	-0.27	-0.21	-0.03	0.20	0.39	0.55
EP (four passive traders):	-0.14	-0.14	-0.14	-0.14	-0.21	-0.18	-0.07	0.15	0.34	0.52
EP (five passive traders):	-0.25	-0.25	-0.25	-0.25	-0.25	0.00	0.04	0.21	0.39	0.60
EP (six passive traders):	-0.49	-0.49	-0.49	-0.49	-0.49	-0.49	0.53	0.64	0.79	0.99

Naturally, if T_0 is better off with abandoning fundamental information, other traders will follow him. But, as it is shown in table 2, a passive strategy (as any other strategy) degrades the more, the more traders adopt it. If T_0 switches to a passive strategy, he is better off (-0.10 instead of -0.34), the same holds for T_1 (-0.11 instead of -0.31), for T_2 (-0.12 instead of -0.30), and for T_3 (-0.14 instead of -0.26). For T_4 , however, switching is not anymore benefiting: his EP goes from -0.21 to -0.25; the same is true for traders with higher information levels. It is not feasible that in a market all traders make random (or index-based) choices; as they create more and more noise, there has to be a natural barrier for passive investment strategies (Hanke and Schredelseker, 2010).

As long as we consider only two strategies, active and passive, in table 2 the line with four passive and six active traders represents a Nash-equilibrium: nobody has an incentive to change strategy. As we will see later, there may be other strategies as chartists, deciding not on fundamentals but exclusively on market signals (Schredelseker, 2014) or there may be even chaotic strategies created by genetic algorithms (Hauser and Kaempff, 2013). Always holds that it cannot be rational that all traders follow the same strategy in making investment decisions. Even if most textbooks propose such a unique, information-based strategy, holds: If all traders do the best they can do, the market exhibits diversity in strategies, not uniqueness.

3.3. High standards of public information create private as well as public value

The main rationale for mandatory financial reporting is to reduce the informational gap between well informed and poorly informed investors. It is assumed, that if all agents get access to a considerable amount of relevant information, the decision quality of the less informed should be enhanced and the market should come closer to a fair game. There seems to be no doubt that financial analysis, based on financial reports and other mandatory public information, has private and social value. But there are doubts. It may be true that the valuations of individual traders become more precise if they are better informed, but at the same time, their decisions get more synchronized. According to the International Financial Reporting Standards (IRFS) the financial report should deliver a "faithful representation" of the firm's economic situation. As the financial report is just a subset of all information needed to make good estimations of the firm's value, the best we can expect is, that *on average* this goal is reached: sometimes financial reports will deliver faithful, sometimes too rosy, and sometimes too black painting representations. As financial analysis is taught basically in the same way all over the world, in the case of a biased

report we have to fear that all analysts whose decisions rely on it will make similar misjudgments and thus cause considerable mispricing because they herd. This is why it has been argued that public information is a “double-edged instrument” that on the one hand conveys useful information, but on the other hand “serves as a focal point for the beliefs of the group as a whole” (Morris and Shin, 2020). Table 3 shows this ambiguity in the ABM, where in a market with only information processing agents (=fundamentalists) the public information level (PIL) is enhanced step by step. Starting from PIL0 (as in table 1) the position of more and more binary signals becomes public knowledge (PIL1, 2, 3...). In the first step, only T_0 knows more than he knew before, but he is worse off: now he decides always as T_1 does and both have a stronger impact on the market price than they had with independent decisions. The same happens if PIL is further enhanced till it has reached PIL4. Here all traders who rely upon the public information are worse off as they have been without it; better off are only the traders whose information has remained unchanged. Only from PIL5 on, improvements of public information lead to the desired effect and more public information creates value for its addressees. Newly, we have to do with a nonlinear relationship between information and performance and it is hard to say whether in the real world we are still before or already behind a similar turnaround. Considering that financial reports are mainly retrospective and as such inappropriate instruments to estimate future payoffs of a firm, it is much more likely that we are still before it.

Table 3. Expected payoffs with stepwise enhanced public information.

Trader:	T_0	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9
PIL 0	-0.34	-0.38	-0.40	-0.37	-0.31	0.03	0.22	0.39	0.51	0.64
PIL 1	-0.40	-0.40	-0.38	-0.37	-0.28	0.03	0.24	0.39	0.52	0.64
PIL 2	-0.46	-0.46	-0.46	-0.34	-0.34	0.16	0.24	0.44	0.55	0.67
PIL 3	-0.47	-0.47	-0.47	-0.47	-0.22	0.06	0.36	0.44	0.57	0.68
PIL 4	-0.50	-0.50	-0.50	-0.50	-0.50	0.41	0.27	0.54	0.60	0.69
PIL 5	-0.31	-0.31	-0.31	-0.31	-0.31	-0.31	0.41	0.32	0.53	0.61
PIL 6	-0.18	-0.18	-0.18	-0.18	-0.18	-0.18	-0.18	0.31	0.36	0.56
PIL 7	-0.08	-0.08	-0.08	-0.08	-0.08	-0.08	-0.08	-0.08	0.25	0.39
PIL 8	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	0.25
PIL 9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Even if public information may be of dubious value for the traders, it could be argued that any public information increases the average knowledge in the market and this leads to a social desideratum, to a market being informationally more efficient. But this ignores the impact of synchronized decisions on the market price. In the ABM, market efficiency can easily be calculated as the variance of mispricing $\sigma^2(P-V)$. As T_9 knows everything what is knowable, his estimation $E_9(V)$ represents the intrinsic value V° with $V=V^\circ\pm 0.5$. As the last signal is unknown to everybody, the highest level of market efficiency is $\sigma^2(V^\circ-V) = 0.25$: the market fully reflects all available information. The more $\sigma^2(V-P)$ exceeds 0.25, the more inefficient the market will be.

Table 4. Market efficiency related to different levels of public information.

Public Information Level:	PIL 0	PIL 1	PIL 2	PIL 3	PIL 4	PIL 5	PIL 6	PIL 7	PIL 8	PIL 9
Market efficiency $\sigma^2(V-P)$:	1.02	1.02	1.07	1.09	1.16	0.93	0.73	0.56	0.50	0.25

Table 4 shows that with enhancing the public information level, market efficiency decreases up to a certain point (till PIL4), thereafter it increases. Like the value of private information the worthiness of public information too, is not linearly related to its level. Looking from a market perspective, two things are opposing: even if a higher level of public information may reduce the information spread between bad and good informed traders, this is not necessarily beneficial for its addressees as it increases undesirable herding.

3.4. Highly skilled financial analysts usually decide better than their unqualified colleagues

Whatever we do, it is common wisdom that it is the better done, the more skilled and the more experienced we are. This holds in arts, in technology, in medicine, in sports, etc. But does it likewise hold for a financial analyst deciding in a complex market environment? As mentioned above, a financial report should deliver a “faithful representation” of the firm’s economic setting, but, being just a subset of all information that is necessary, this target is at best reached on average. Mostly it will not be the case: for various reasons the representation of the firm’s fair value by the financial report is $R = V \pm \delta$, where δ (assume $\mu_\delta=0$) denotes accounting imperfections due to legal restrictions, to unforeseeable external effects, and/or to creative accounting. But the object of financial analysis is R and not V ; you can analyze only what you get and not what you would like to get. Furthermore, estimating V based on R is subject to a certain diffuseness; even if having the same informational input, different analysts will come to different individual perceptions. It may be assumed that the estimations of the firm’s intrinsic value $E_i(V)$ are unbiased to R , but surely they are different in precision. Highly skilled and experienced analysts will capture the pure signal R more precisely than inept analysts do. If the estimation of an analyst results to be $E_i(V)=R \pm \varepsilon_i$ (with assumed $\mu_\varepsilon=0$), $\sigma^2_{\varepsilon_i}$ stands for his idiosyncratic professional quality; the smaller $\sigma^2_{\varepsilon_i}$ is, the closer to R will be $E_i(V)$, the estimation of analyst i . With respect to the fair value V , however, analyst i ’s estimation is $E_i(V)=V \pm \delta \pm \varepsilon_i$. It is subject to two error terms: δ , due to accounting imperfections, and ε_i , due to the analysts’ idiosyncratic imperfections in interpreting R . There is no reason to assume that the two error terms may in any way be correlated.

In a market with well-informed traders (insiders and some investors spending huge sums for professional financial research) and analysts deciding mainly upon the public information, the first will estimate rather $E_i(V)=V \pm \varepsilon_i$ and the latter rather $E_i(V)=R \pm \varepsilon_i$. Therefore, to match supply and demand, the market usually will clear with $V > P > R$ if $V > R$, with $V \approx P \approx R$ if $V \approx R$, or with $V < P < R$ if $V < R$. In all cases with $V \neq R$ good informed traders will be more likely on the right side of the market: they mostly buy if $V > P$ and mostly sell if $V < P$. Analysts, however, who decide upon public information will rather be on the wrong side: they mostly buy if $V < P$ and mostly sell if $V > P$ (Schredelseker, 2023). Furthermore, in the group of those who rely upon public information R , holds: the less an analyst is qualified, the better his performance is expected to be, because he makes mistakes in making mistakes. The probability that his idiosyncratic ε overrules the generic δ is the higher, the larger $\sigma^2_{\varepsilon_i}$ is. This is evidenced in table 5 where we show an ABM with PIL5 and all ten traders deciding as fundamentalists. The traders $T_0 \dots T_5$ get the same message R (=the first five binary signals), but they are different in their ability to interpret it; the message they get is overlaid by a noise parameter being equally distributed between $-d$ and d . So, with respect to R , trader T_0 makes the most inaccurate estimates, whereas T_5 makes no mistakes at all. Nevertheless, he pays for his exactness with the lowest expected payoffs in his group, because he does not make mistakes in making mistakes.

Table 5. Traders using the message PIL5 are different in their precision.

Trader t:	T_0	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9
d (noise parameter)	1.0	0.8	0.6	0.4	0.2	0.0				
EP with PIL 5	-0.19	-0.22	-0.24	-0.34	-0.41	-0.44	0.32	0.28	0.59	0.65

In a financial market, it is not precision what is rewarded, but the probability to end up on the winning side of the market.

Consider a very simple example: Six agents trade a security with true value $V=8$. Their estimations of the value are 3, 6, 6, 8, 13, and 15. As they want to buy/sell if they believe the security to be under-/overpriced, the clearing price will be 7 and the security will be underpriced. The first three traders sell and lose, and the last three traders buy and win. With respect to the true value $V=8$ the winners made an average error of 4 and the more precisely estimating losers only of 3.

A trader's total estimation error $\sigma^2_{(\delta+\epsilon_i)} = \sigma^2_\delta + \sigma^2_{\epsilon_i}$ is the lower, the lower $\sigma^2_{\epsilon_i}$ is; the estimations of traders with a small $\sigma^2_{\epsilon_i}$ are more precise with respect to the true value V . But as a highly-skilled trader usually assesses a given signal close to its informational content, he is more likely on the loser's side than his unqualified colleague who often makes mistakes in assessing a biased signal. Therefore, professional excellence may not be what counts in a complex system as a financial market.

3.5. The market becomes less efficient if traders miss out on information

The informational efficiency of a financial market depends on the willingness of the market participants to proceed with information. This is widely accepted and follows conjecture 1 of the seminal Grossman and Stiglitz paper (1980): 'The more individuals who are informed, the more informative is the price system.' In a recent paper, this is confirmed arguing that, if more and more people abandon information, they create noise and noise will overlay the price signal creating inevitable inefficiencies (Israeli et al., 2017). Another paper, however, found rather an increase in market efficiency with growing ETF activities (Glosten et al., 2021), but the authors remarked that the effect of ETF activity on informational efficiency is still an open question. We believe that our ABM could deliver a fruitful contribution to this debate. In table 2 we have examined whether a trader who switches from a fundamental to a passive investment strategy is better off or not; we evaluated his private value of information. In the sequel we are interested in the public value, measured in terms of market efficiency σ^2_{V-P} . In table 6 we observe that if more and more traders abandon their information and decide randomly, firstly the market becomes informationally more efficient and efficiency reaches its maximum with five passive traders ($T_0...T_5$); then inefficiencies increase rapidly. But even if seven out of ten agents do not trade upon information, the market is still more efficient as with all traders deciding as fundamentalists. Obviously, it is not the number of informed traders that drives market efficiency.

Table 6. Market Inefficiency with more and more Passive Traders.

N° passive Traders	0	1	2	3	4	5	6	7	8	9
EP with PIL 5	1.02	0.93	0.83	0.75	0.66	0.60	0.65	0.85	1.20	1.67

The nonlinearity is easy to explain. If more and more traders switch from a fundamentalist to a passive strategy we have to assume that rather low-informed traders are the first to do so; thus, we get two opposing effects. On the one hand, the average information level of the remaining traders is increasing, while the herd of traders who decide on possibly biased information becomes smaller. This leads to a higher informational efficiency of the market. On the other hand, more passive traders create more noise which overlays the price signal created by the fundamentalists; this has a negative impact on market efficiency. Considering both effects, market efficiency firstly increases; from a certain point on, the noise created by non-information-based traders prevails and makes market efficiency decrease. Similar non-linear results have been obtained with other non-information-based strategies such as chartists or a mix of passive traders and chartists (Schredelseker, 2014). The most impressive results, however, are presented in an ABM based upon genetic programming (Hauser and Kaempff, 2013): In their model, too, a security is traded whose value is the sum of ten binary signals, but they consider 100 agents in ten groups with ten agents each. Information is asymmetric as in any group $n_{0...9}$, the agents know the first n signals $S(0,1)$. All agents start trading as fundamentalists who estimate the security's value as $E_n(V) = \sum_{j=1}^n S_j + (10-n)/2$ and give their respective orders. Naturally, the result is the same as in table 1, now with the first ten traders having an EP of -0.34 each, the second with an EP of -0.38 ... and the best ten traders of 0.64 each. Starting with that, in the genetic programming procedure a trader is picked up by random and, like in biological evolution, mutates the original decision rule applying some algebraic operators (e.g. +, -, *, /, >, <, RANDOM, IF THEN). If the new algorithm

performs better, it replaces the previous one; if not, it is abandoned. Repeating this 500 times, any of the 100 agents have at least once run the procedure and choose the strategy which is best for him; the algorithms found by such a procedure are very different and often hard to interpret. Only the cohort with the highest information level (IL9) is homogeneously deciding upon its information; even if IL₉-traders have been picked up to improve their fundamentalist decision strategy, they did not succeed. What all others, the non-top-informed traders have in common, is to avoid herding: do not do what others do. The authors show that any strategy, whatever it may be, loses quality if it is copied by others (Hauser and Kaempff, 2013). The overall result is striking: If all agents do the best they can do, i.e. if all but the top-informed refuse to adopt the fundamentalist strategy, the market comes with $\sigma^2(P-V) = 0.27$ remarkably close to full market efficiency with $\sigma^2(P-V) = 0.25$. The losers, instead of losing up to -0.40 while processing information, now lose only about -0.005; the winners, instead of winning 0.64, now win only 0.05. When Hellwig (1982) stated that “the market will approximate full informational efficiency arbitrarily closely” he had in mind a special kind of rational expectations. The results in table 7 are based upon another rationality: the rationality of not to follow the rules that traders in textbooks of financial analysis are asked to follow.

Table 7. Information based strategy vs. optimal strategy: performance compared.

Ten traders on any IL _n	IL ₀	IL ₁	IL ₂	IL ₃	IL ₄	IL ₅	IL ₆	IL ₇	IL ₈	IL ₉
All traders decide as fundamentalists	-0.34	-0.38	-0.40	-0.37	-0.31	0.03	0.22	0.39	0.51	0.64
Only IL ₉ -traders are fundamentalists	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	0.05

Obviously, the information generated by the best informed traders and conveyed in the market clearing price is good enough to enable all others to free-ride. If traders refuse to proceed with information, they take no more part in a competition where they are bound to herd. They refuse to be more likely losers than winners. The statement in the Grossman and Stiglitz paper refers only to quantity, but quality seems to be much more striking. Shouldn't it be rewritten as “The more individuals, except the very best, are informed, the less informative is the price system.”? It is sufficient, that there is a small group of excellently informed traders to make market prices informative; all others just create noise.

3.6. To use Bayes' updating rule means to make rational financial decisions

Bayes' updating rule is in the kernel of current financial decision theory. If we have a belief (*prior*) about the problem to be resolved and we know how likely received empirical data signal the probabilities of these data (*likelihoods*), we can combine both to an opinion of higher quality in the sense of being closer to truth (*posterior*). The algorithm to do so is the well-known formula of Thomas Bayes (1701-1771). As in financial economics for decades prevailed a natural science paradigm, adopting Bayes' rule for financial decisions seemed to be straightforward. Even Shefrin and Statman (1994) developing their ‘Behavioral Capital Asset Pricing Theory’ distinguishes information traders who ‘use a proper Bayesian learning rule’ from noise traders, who ‘commit errors as they employ non-Bayesian rules’. But, can the transfer from natural sciences, where Bayes' algorithm originally comes from, to market decisions be done so easily? We believe that this is not the case.

Financial textbooks typically illustrate and explain the use of Bayes' rule in terms of an example. Usually, the exemplified trader has an opinion, gets new information, knows its likelihood, and updates this opinion to a higher cognitive level. But, can we truly be confident in the information we get? In engineering (or other decisions against nature), before we get informed, we know nothing. Any new information improves our knowledge or it is worthless; if we disregard counterfactual information, there is a linear advancement from ignorance to knowledge, the more we know the better it is. In financial markets, however, we do not start at zero. Knowing the market price, we already know a lot. We know that it is equally likely that this price is too high or too low with respect to the unknown

intrinsic value of the asset. Before we get new information, this abeyance is necessarily our *prior*. We know also, that the market price divides up the whole set of information in two equally weighted parts: only if there is roughly as much reason in favor of an overpricing as in favor of an underpricing, the market will be cleared. Any new signal we get may have its origin in the first or the second subset, we do not know. So, we do not know whether the signal we get is improving or degrading our prior: the first is the case if the security is under-/overvalued and we get a bullish/bearish signal, the second is the case if the security is under-/overvalued and we get a bearish/bullish signal.

If M denotes the actual market mispricing with the possible specifications *over* or *under* and if S denotes the trader's signal with the possible specifications *bull* (underpricing is signaled) or *bear* (overpricing is signaled) we get the well-known Bayes' formula with

$$p(M|S) = p(S|M) * p(M)/p(S)$$

For the financial community as a whole, the unconditioned probability $p(M)$, with the cases $p(\textit{over})$ or $p(\textit{under})$, has to be $p(M)=0.5$; we cannot assume that the market is systematically over- or underpricing its assets. The unconditioned probability $p(S)$, with the cases $p(\textit{bear})$ or $p(\textit{bull})$, is also $p(S)=0.5$, as otherwise the market will not be cleared. Thus, after canceling the two unconditioned probabilities, the formula reduces to the *posterior*.

$$p(M|S) = p(S|M)$$

where the conditional probability $p(M|S)$ equals the likelihood $p(S|M)$. It is the same, whether you ask, how is the security probably priced if you get a bearish or bullish signal, or if you ask, what type of signal we probably get, if the security is over- or underpriced; in both cases, the answer will be 0.5.

If, however, we consider asymmetric information with some extremely well informed and a huge number of medium/low informed investors, it is not just a matter of fortune, whether an investor is more likely among the winners or the losers, but it depends on his merits: his experience, his market understanding, and perhaps most importantly, his information achieved by costly information acquisition. If we combine all these attributes in a single indicator EI (economic intelligence), we can split up the community of investors in two halves with equal market volumes: a small group of agents whose EI is above average and a very large group of agents whose EI is below. Because of their superior skills, the first will get signals being rather right than wrong: they will rather go long if the security is underpriced, and rather go short if it is overpriced. Correspondingly the big majority of traders, those with EI under average, take the opposite position: more often they get pushed on the losing than on the winning side of the market. This is not because their information is false, even if it may be undoubtedly material, it is just inferior in quality compared to the information of the best informed. In the ABM we have seen that trader T_2 gets correct information and $E_2(V)$, his estimation of V , becomes undoubtedly more precise than the estimation of T_1 ; nevertheless, as he follows widespread public information he cannot avoid herding, which makes him worse off. Table 8 shows the likelihood of the signals traders receive under the condition of a given market clearing price.

Table 8. Signaling probabilities for traders with EI above (a) or below (b) average.

Traders with EI above average get a .			Traders with EI below average get a .		
	..bearish signal	..bullish signal		..bearish signal	..bullish signal
if security is overvalued	$p_a(S)>50\%$	$p_a(S)<50\%$	if security is overvalued	$p_b(S)<50\%$	$p_b(S)>50\%$
if security is undervalued	$p_a(S)<50\%$	$p_a(S)>50\%$	if security is undervalued	$p_b(S)>50\%$	$p_b(S)<50\%$

For the big majority of traders, using *Bayes'* formula moves them not only directionless away from their prior abeyance, but drives them predominantly in the wrong direction. A possible solution to avoid this trap could be the rule of Paul Arden's book *Whatever You Think, Think the Opposite*. However, psychology tells us that rational decision makers cannot execute such a maxim without getting in material mental troubles. You cannot seriously

believe the contrary of what you are believing.

4. Conclusions

The heuristic driver of this paper is a purely individualistic approach in the tradition of the Austrian school of economics, where social phenomena have to be explained primarily by the actions and interactions of self-interested individuals; these individuals are different in wealth, talents, preferences, and especially in knowledge. The most powerful approaches to capture interaction in social sciences (and not only there) are computer simulations and agent based modeling. When about 25 years ago Levy et al. (2000) published their book on microscopic simulations, *Markowitz*' wrote in a blurb, that this approach "point us towards the future of financial economics. If we restrict ourselves to models which can be solved analytically, we will be modelling for our mutual entertainment, not to maximize explanatory or predictive power." Agent-based modeling is surely not a panacea for financial economics, but in analyzing complex systems like financial markets, it has tremendous advantages to classical closed-form models. The agents in the simple ABM presented here

- interact within the market network (they don't make isolated optimizations)
- act as autonomous decision makers (there are no aggregations or representative agents)
- do the best they can do (no noise traders or other silly agents are needed)
- follow simple rules (results are not driven by assumptions on highly sophisticated agents)
- are intelligent and purposeful (they have no cognitive biases or emotions)
- use strategies being the best answer to the strategies of others (Nash equilibrium)
- have different information and/or come to different beliefs with the information they have
- produce market clearing prices (all agents are price-makers and not price-takers)
- procure results which are not predetermined in the model design (emergence).

The model is extremely simple and easily reproducible, but rich enough to capture a niggles of the complexity that tags a financial market. If we want to understand it, we have to accept its complexity, its nonlinearities and its reflexivities. The main focus of this paper is on information, on the nonlinear relationship between information level and decision quality, the nonlinear relationship between an analyst's skills and his performance, the nonlinear relationship between market efficiency and the number of investors doing financial analysis, the nonlinear relationship between better disclosure laws and their impact on the addressees of public information. In all these cases it has been shown that the widespread wisdom of a "the more the better" merits to be seriously questioned. The future of financial economics depends on whether we accept that financial decisions are not decisions against nature. If it were, the conventional engineering approach, based primarily on individual optimizing, could be adequate. But it is not.

Funding Statement

This research received no external funding.

Acknowledgments

Acknowledgments to anonymous referees' comments and editor's effort.

Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

Author contributions

Conceptualization: Klaus Schredelseker; Investigation: Klaus Schredelseker; Methodology: Klaus Schredelseker; Writing – original draft: Klaus Schredelseker; Writing – review & editing: Klaus Schredelseker.

References

- Bachelier, L. (1900). Théorie de la Spéculation. *Annales scientifiques de l'École Normale Supérieure, Serie 3*, 17(1900), 21-86. <https://doi.org/10.24033/asens.476>
- Easley, D., and M. O'Hara. (2004). Information and the Cost of Capital. *Journal of Finance*, 59, 1553-1583. <https://doi.org/10.1111/j.1540-6261.2004.00672.x>
- Glosten, L., Nallareddy, S., and Zou, Y. (2021). ETF activity and informational efficiency of underlying securities. *Management Science*, 67(1), 22-47. <https://doi.org/10.1287/mnsc.2019.3427>
- Grossman, S., and Stiglitz, J. (1980). On the Impossibility of Informationally Efficient Markets. *American Economic Review*, 70, 393-408. <https://doi.org/10.2139/ssrn.2433662>
- Hanke, M., and Schredelseker, K. (2010). Index funds should be expected to underperform the index. *Applied Economic Letters*, 17, 991-994. <https://doi.org/10.1080/17446540802599689>
- Hauser, F., and Kaempff, B. (2013). Evolution of trading strategies in a market with heterogeneously informed agents. *Journal of Evolutionary Economics*, 23, 575-607. <https://doi.org/10.1007/s00191-011-0232-6>
- Hayek, F. A. (1945). The use of knowledge in society. *American Economic Review*, 35, 519-530. <https://doi.org/10.1017/cbo9780511817410.007>
- Hellwig, M. (1982). Rational Expectations Equilibrium with Conditioning on Past Prices; a Mean Variance Example. *Journal of Economic Theory*, 26, 279-312. [https://doi.org/10.1016/0022-0531\(82\)90005-9](https://doi.org/10.1016/0022-0531(82)90005-9)
- Hule, R., and Lawrenz, J. (2008). The Value of Information, in: Huber/Hanke (Ed.), *Information, Interaction and (In)Efficiency in Financial Markets*, Vienna (Linde), 135-155. https://doi.org/10.1007/978-3-540-70556-7_8
- Israeli, D., Lee, Ch., and Sridharan, S. (2017). Is There a Dark Side to Exchange Traded Funds? An Information Perspective. *Review of Accounting Studies*, 22, 1048-1083. <https://doi.org/10.1007/s11142-017-9400-8>
- Levy, H., Levy, M., and Solomon, S. (2000). *Microscopic Simulation of Financial Markets: From Investor Behavior to Market Phenomena*. Academic Press, 2000, 183-198. <https://doi.org/10.1016/b978-012445890-1.50009-1>
- Markowitz, H. (1952). Portfolio Selection. *Journal of Finance*, 7, 77-91. <https://doi.org/10.1111/j.1540-6261.1952.tb01525.x>
- Morris, S., and Shin, H. (2002). Social Value of Public Information. *American Economic Review*, 92, 1521-1534. <https://doi.org/10.1257/000282802762024610>
- O'Hara, M. (2003). Liquidity and Price Discovery. *Journal of Finance*, 58, 1335-1354. <https://doi.org/10.1111/1540-6261.00569>
- Pfeifer, C., Schredelseker, K., and Seeber, G. (2009). On the negative value of information in informationally inefficient markets: Calculations for large number of traders. *European Journal of Operational Research*, 195, 117-126. <https://doi.org/10.1016/j.ejor.2008.01.015>
- Schredelseker, K. (2014). Pascal's Wager and Information. *Journal of Forecasting*, 33, 455-470. <https://doi.org/10.1002/for.2300>
- Schredelseker, K. (2023). Back to the Roots. *Journal of Portfolio Management*, 50, 128-136. <https://doi.org/10.3905/jpm.2023.1.544>
- Shefrin, H., and Statman, M. (1994). Behavioral Capital Asset Pricing Theory. *Journal of Financial and Quantitative Analysis*, 29: 323-349. <https://doi.org/10.2307/2331334>