

The Strength and Weight of Information and Investor Confidence in Financial Markets

Grzegorz Mardyla*

Abstract

The purpose of this paper is to analyze the market reaction to the existence of traders affected by biased confidence, whose confidence is in turn dependent on particular traits of the information they observe, namely its strength (saliency), and weight (statistical significance). *Confidence function* is introduced as a way of formalizing the relationship between different attributes of information and confidence. We show in a simple setting that if investors' confidence is affected by information strength and information weight, then prices exhibit delayed overreaction to information events; this overreaction may continue for a prolonged period of time. Furthermore, as more and more information is introduced, uncertainty might increase among irrational investors and prices tend to underreact to ambiguous news. We also examine the resulting implications for market liquidity and price efficiency. In another case based on a generalized setting, we learn that depending on the intensity of irrational trading, prices exhibit positive serial correlation when there are few miscalibrated traders in the economy or their bias is moderate; prices overreact to news if the opposite conditions are met.

1 Introduction

Substantial body of evidence from experiments suggests that people are “miscalibrated” when making decisions in uncertain environments. Miscalibration is a term used to describe errors in confidence. We are miscalibrated if our beliefs regarding the correctness of our estimate of an unknown variable depart from rational, given the available information. This article argues that if we take into account the relationship of biases in confidence with the information structure of the economy, we not only end up with fuller understanding of the role of bounded rationality and information in financial markets, but also with some conclusions that extend the results of previous research. In addition to that, given the emphasis on information, we are able to generate some interesting empirical

*Kinki University, Faculty of Economics. greg@kindai.ac.jp

implications regarding dynamical patterns in asset prices.

Two factors will play main roles in our analysis: investor confidence and information, in particular the strength and weight of information. Our approach is motivated by experimental evidence documented in Peterson and Pitz (1988) [18] as well as Griffin and Tversky (1992) [12]. They find that when evaluating the impact of new information, “people are overconfident when (it’s) strength is high and weight is low, and underconfident when (it’s) strength is low and weight is high¹⁾”.

Interpreting these results with a financial market framework in mind leads us naturally to question the relevance of relationship between information and confidence for the behavior of asset prices. According to the above findings, individuals with strong signals about the underlying value of the asset should be overconfident in the quality of their signals. On the other hand, those with low-strength, high-weight signals should exhibit underconfidence with respect the quality of their signals.

If we want to formalize the relationship between confidence and different information characteristics, the first step is to actually define what constitutes *strength* and *weight* of information. Our setup should be consistent with the results of experiments performed by Griffin and Tversky (1992) [12] and also those by Nelson et.al. (2001) [16]. The latter article presents an experimental study of the effects of information strength and weight designed specifically with financial markets in mind. Briefly summarizing their technique, high-strength, low-weight information is represented by a small number of fair coin flips with the same results (e.g. 3 coin tosses with 3 heads), while low-strength, high-weight information typically consists of a large number of coin tosses with a small differential between the number of heads and tails (e.g. 17 coin tosses with 10 heads²⁾).

The rest of this paper is organized as follows. In the next section, we introduce some evidence from the cognitive psychology literature that motivates our analysis of the interrelation between confidence and information. Section 3 reviews extant related literature that applies biased confidence in financial settings. We present the main ideas and results of this paper in Section 4, where we also motivate our setup with intuitive examples. We discuss robustness issues and some extensions in Section 5 and finish with a conclusion and suggestions for further research.

2 Evidence on Information and Confidence

Experiments in cognitive psychology and economics aimed upon identifying systematic biases in individual decision making under uncertainty abound in examples of over- and underconfidence, often with respect to various types of information. Apparently, we humans are not neutral, rational information processors but tend to overestimate the weight of given evidence in some contexts while underestimate the significance of the data at hand in other contexts. In this section we introduce some important experimental work on biases in confidence and discuss their implications and validity when evaluated in

relation to information within an economy. We focus on articles that allow for qualitative considerations of information, confidence, uncertainty, and the relationships between the three phenomena.

Overconfidence and *excessive certainty* are two terms often treated as equivalent, particularly in applications to financial economics: an agent's ability to predict the accuracy of his judgment (confidence) is dealt with similarly or in exactly the same manner as an agent's beliefs regarding possible values of an unknown variable (uncertainty). Peterson and Pitz (1988) [18] provide evidence that confidence and uncertainty are in fact two distinct cognitive phenomena and are affected in different ways by the available information. The difference between confidence and uncertainty can be thought of as a counterpart to the difference between hypothesis generation and hypothesis testing. To put it another way, when we are to predict an event, our uncertainty can be assessed based on generation of possible outcomes, whilst our confidence is assessed whenever we evaluate a hypothesis that has already been put forward.

A particularly striking result from Peterson's and Pitz's (1988) [18] study is that uncertainty increased with increased amount of information, which is contrary to the predictions of statistical theory. This increase in uncertainty is shown to be caused by inconsistent information, such that may suggest conflicting outcomes. Confidence, on the other hand, increased with more information in the experiments administered by the authors. However, confidence decreased significantly on the individual level in response to more difficult tasks. Another noteworthy result showed that confidence was found to be affected by salient but irrelevant information and not affected by nonsalient yet relevant information. The two phenomena are not totally distinct — they are shown to be correlated with each other and the level of correlation to be a function of the way information was provided; it is crucial whether information is used to generate hypotheses or to evaluate previously stated hypotheses.

In a related study, Griffin and Tversky (1992) [12] focus explicitly on how different attributes of information affect judgments of confidence. They find that the main determinant of confidence is the relation between the strength and the weight of available evidence. Strength is understood to stand for extremeness or salience of information, while weight represents its statistical significance or credence. The main conclusion is that people are overconfident when strength is high and weight is low, and underconfident when strength is low and weight is high. The experiments suggest that confidence is determined by the balance of arguments for and against conflicting propositions, with insufficient regard for the weight of the evidence. Even though Griffin and Tversky (1992) [12] do not attempt an analysis of the distinctions and possible relationship between confidence and uncertainty, their decisive results provide much insight into the way people's confidence evolves in response to different information. In particular, they show it is not only overconfidence that is prevalent; underconfidence is also a common occurrence in uncertain environments, mainly ones characterized by complicated information structures.

It is noteworthy that the notions of the strength and weight of information discussed by Griffin and Tversky (1992) [12], and, in general, the concept of *evidence weight*, have its origins in the work of Keynes (1921) [15], who distinguished between *probability*, which represents the balance of evidence in favor of a particular proposition and *weight of evidence*, representing the quantity of evidence that supports that balance. In this paper we follow the extant behavioral finance literature that uses over- and underconfidence to mean both erroneous confidence and excessive certainty/uncertainty.

3 Related Literature

Perhaps two papers closest in focus to the present one are Bloomfield et.al.(2000) [5] and Bernardo and Welch (2001) [3]. Reliability of information is the focus of a study by Bloomfield et.al.(2000) [5]. They motivate their experimental setup with a straightforward representative investor model of Bayesian learning. The investor has access only to a noisy signal about the accuracy of his information, which leads her to overestimate the reliability of highly unreliable information and underestimate the reliability of highly reliable information. The authors refer to this phenomenon as *moderated confidence* — confidence moves toward an average, yet insufficient level. In two experiments designed to test the model, Bloomfield et. al. (2000) [5] provide investors with perfect information regarding the reliability of their signals. Nevertheless, the resulting asset prices are found to exhibit persistent deviations from fundamental values: the markets underreact more to information of high reliability than to information of low reliability. Another finding is that extreme prices are observed: high prices are too high, and conversely, low prices are too low. An interesting insight into the outcomes of the experiments is that investors do not actually overreact to information; rather, unreliable information produces moderate overreaction, but reliable information gives rise to large underreactions. Effectively, it is possible that prices in a setting with conflicting news of differential reliability move in the wrong direction altogether.

Informational cascades are the background of a model used to explain the persistence of overconfident behavior to be found in a paper by Bernardo and Welch (2001) [3]. When information aggregation within a population is poor, overconfident individuals — entrepreneurs — can mitigate the negative effects of herding behavior by conveying valuable private information. In doing so, they act altruistically: irrational choices adversely affect their welfare but they help the overall well-being of the group. Conditions are identified under which the costs born by entrepreneurs are low while keeping the benefits to the overall group high. Groups with sufficient amount of activity caused by overconfident entrepreneurs are shown to have an evolutionary advantage over groups without such individuals so that in equilibrium overconfidence survives.

The paper explains the long-run existence of agents who follow their own information. However, the attributes of this information in no way influence the agents' choices; thus

the evidence of Griffin and Tversky (1992) [12] is not taken into account in this model—the overconfident always follow their own information with no regard to its strength and/or its weight.

4 Information and Confidence in Financial Markets

In recent years, a number of financial market models with overconfident traders have been proposed. Typically, overconfidence is assumed exogenously in the form of excessive certainty, i.e. tightness of a distribution function of an unknown variable. This, in effect, is equivalent to overvaluing the precision of one's information. It is often the case that little attention is given to possible causes of miscalibration—overconfidence is taken as a primitive fact about the behavior of individuals. It appears that there may be a bias among economists as to which biases evidenced in the cognitive psychology literature to emphasize and utilize. Though overconfidence is documented to be a pervasive error in decision making, it often stems from more primitive variables in the economy, notably from the structure of uncertainty and information. Also, miscalibration does not manifest itself only as overconfidence; in numerous cases, underconfidence has been observed yet its implications for behavior in financial market settings have been largely ignored. In this section, we develop a simple model where the perceived precision of investor information changes due to informational effects.

The flow of information affects the way agents in an economy view investment opportunities. Information may arrive in many different ways and can accordingly be interpreted differently by heterogeneous individuals. Extreme informational signals are processed differently than signals that are closer to their *ex ante* expected values. Sequences of signals may provide more information than a single one—good news that follows bad news might result in an updated belief that may contrast with the belief resulting from a sequence of bad news following good news. Beliefs themselves may be updated in various ways depending on the length of time or the number of information events since first signals were received. In general, confidence comes into play when agents update their beliefs regarding uncertain variables in the economy in response to a sequence of informational signals.

An appropriate signal structure that would allow for modeling information strength and information weight should preferably be a multiple-signal environment. A convenient feature found in a class of models is signals additivity—whenever an outcome of a series of signals can be summarized by one value, e.g. when a series of two good signals and a bad one is equivalent to one good signal. Stylized models that exhibit this feature include Harris and Raviv (1993) [14], who allow their signals to be drawn from a real line, and Chari and Kehoe (2004) [9], where signals are binary. Yet additivity alone is insufficient for our purposes—the total number of signals received is also important. Furthermore, we wish to focus our attention on the interrelation between information structures and

investor confidence. The modeling choices we make have to be consistent with the experimental evidence presented above.

Consequently, we postulate a general form of a *confidence function* below that depends on a sequence of signals and their number, or time since the beginning of information generation process. Let time be indexed as a discrete sequence of periods $t=1, 2, \dots$. The confidence function K is thus defined by

$$\bar{K}_t = K(s^t, t),$$

where $s^t = (s_1, s_2, \dots, s_t)$ represents a sequence of signal realizations. Depending on a specific model, the confidence function should be assumed to take a particular form, consistent with the evidence on decision making under uncertainty from the cognitive psychology literature.

4.1 Gaussian Random Variables and Exponential Utility

We develop our framework around the model of Vives (1995) [20]. While he considers both short-term and long-term investment horizons, we focus on long-term investment, as it is more appropriate given our aim of analyzing dynamic effects of confidence and information. We consider a simple multiple period economy — there is one risky asset with random fundamental value v and one riskless bond with unitary return. The fundamental value is assumed to follow a normal distribution with mean \bar{v} and variance σ_v^2 . We shall denote such a distribution $N(\bar{v}, \sigma_v^2)$. It will be convenient to work with precisions instead of variances: let $\tau_\xi = 1/\sigma_\xi^2$ denote the precision of a random variable ξ . Trading takes place over T time periods; at $T+1$ the risky asset is liquidated and its value v realized. To focus on the interplay of information and investor confidence, we assume that there exists a continuum of privately informed identical risk-averse agents of mass one. An informed trader receives at the beginning of period t a signal about the random final payoff in the form $s_t = v + \epsilon_t$, where ϵ follows $N(0, \sigma_{\epsilon_t}^2)$ and is uncorrelated across periods as well as with other random variables. Informed traders remember all signals received up to the present. In any period t an informed agent will thus be in possession of a vector of private signals $s^t = (s_1, s_2, \dots, s_t)$. There are also noise traders present in the market at any period; their demands are formed for reasons exogenous to the model and are thus given by an independently identically normally distributed process $\{u_t\}_{t=1}^T$, which is assumed to be also independent of all other random variables. Investors interact with competitive risk-neutral market makers, who set the price to the expected value of the final payoff. Informed investors are assumed to maximize expected utility of final wealth $W_T = \sum_{k=1}^{T-1} (p_{k+1} - p_k)x_k + (v - p_T)x_T = \sum_{k=1}^T \pi_k$. The utility function is thus given by $E[U(W_T)] = -E[\exp(-\rho W_T)]$, where ρ is the coefficient of constant absolute risk aversion. In what follows, we normalize $\bar{v} = 0$ and $\rho = 1$, without loss of generality.

The Confidence Function

Typically, in CARA-Gaussian models, overconfidence is modeled either by a direct assumption on a biased value of investor's information precision, or as a multiplier of the precision. We thus follow the literature and assume that investor confidence affects her beliefs in such a way that she multiplies the precision of her private information signal by the confidence function. Formally, while the original precision is given by τ_{ϵ_t} , the precision believed to be true by a confidence-biased investor is $K_t(s^t, t)\tau_{\epsilon_t}$. We abstract for now from an analysis of implications of particular forms of the confidence function to focus first on general properties of the model with K as a function of time and of the vector of signals, i.e. $K_t=K(s^t, t)$. Given the evidence regarding strength and weight of information and the assumed normal distributions of random variables, the confidence function has to exhibit certain properties, namely:

1. At $t=0$, $K_t=1$: no over- or underconfidence from the outset. It only arises in response to specific information.
2. $0 \leq K_t < \infty$ for $t \geq 2$: in general, K_t , as a multiplier of precision is allowed to take any nonnegative value.
3. For $\bar{s}_t = t^{-1} \sum_{k=1}^t s_k$, $\frac{\partial K}{\partial (\sum_{k=1}^t |s_k - \bar{s}_t|) / t} < 0$: confidence increases with more extreme, salient signals (or a string of concentrated signals) and decreases with a series of dispersed signals.
4. $\sum_{k=1}^t s_k \rightarrow 0 \Rightarrow K \leq 1$: uncertainty increases — resulting in underconfidence — when conflicting signals are received.
5. $\lim_{t \rightarrow \infty} K = 1$: eventually, the value of the asset is known with enough accuracy so that miscalibration disappears.

It is natural in this setting to define information of high strength and low weight as a realization of a sequence of signals such that $(\sum_{k=1}^t |s_k - \bar{s}_t|) / t \leq \underline{l}$ and $t \leq m$; analogically, high-weight low-strength information is characterized by $(\sum_{k=1}^t |s_k - \bar{s}_t|) / t \geq \bar{l}$ and $t \geq n$, where $\bar{l}, \underline{l}, m$, and n are appropriate cutoff values.

Equilibrium

It follows from the properties of Gaussian random variables that a sufficient statistic for s^t is

$$\hat{s}_t = \left(\sum_{k=1}^t \tau_{\epsilon_k} \right)^{-1} \sum_{k=1}^t \tau_{\epsilon_k} s_k. \tag{1}$$

The equilibrium price and individual (symmetric) demand functions are then calculated using standard methods, and are given as follows.

$$p_t = \lambda_t z_t + (1 - \lambda_t \Delta a_t) p_{t-1} = \frac{\tau_u \sum_{k=1}^t \Delta a_k z_k}{\tau_t} \tag{2}$$

$$x_t = a_t (\hat{s}_t - p_t) = K_t \left(\sum_{k=1}^t \tau_{\epsilon_k} \right) (\hat{s}_t - p_t), \tag{3}$$

where:

- $\lambda_t = \frac{\tau_u \Delta a_t}{\tau_t}$ is the price impact of trade (its reciprocal $1/\lambda_t$ is typically interpreted as a measure of market liquidity);
- $z_t = \Delta a_t v + u_t$ is the order flow at time t ;
- $\tau_t = \tau_v + \tau_u \sum_{k=1}^t (\Delta a_k)^2$ is the t -period conditional precision of the fundamental value;
- $\Delta a_t = a_t - a_{t-1}$ represents the net trading intensity of informed traders, with $a_t = K_t (\sum_{k=1}^t \tau_{\epsilon_k})$.

This unique linear equilibrium is a modification of the one proved in Vives (1995) [20] with the necessary adjustments to incorporate the confidence function. Also, we simplify his model in that in our setting traders receive homogeneous signals. It can be seen now that the constant overconfidence assumption in various models may be exceedingly restrictive; resulting demand functions — and, in particular, trading intensities of informed traders — are in fact contingent on specific sequence of signal realizations and ensuing implications for asset price movements may cease to hold if we notice that confidence depends on the underlying information structure of the economy. In fact, Odean (1998, p. 1901) [17] himself asserts the dependence of investor confidence on the salience of information, although he does not attempt to explicitly analyze it.

In the next subsection, we consider a simple candidate confidence function and proceed to analyze equilibrium price behavior and other variables of interest that result when traders' confidence is affected dynamically by the strength and weight of information.

4.1.1 A Special Case: Four Trading Periods and a Simple Confidence Function

To gain intuition as to how confidence function affects trading strategies and prices, we introduce the following simple example. In the above CARA-Gaussian setup, consider a confidence function with only three possible values: $K \in \{0.5, 1, 2\}$. Neutral confidence is represented by $K=1$, overconfidence by $K=2$, and $K=0.5$ stands for underconfidence. Let there be four trading periods, so that $T=4$, and the risky asset's final payoff is publicly announced at $T+1=5$. In an environment where investors differentiate between good (positive) and bad (negative) signals, let us study a very simple case such that the information strength threshold is equal to two, i.e. when the difference between the number of positive and negative signals is equal or exceeds two, information is viewed as having 'high strength'. In the same manner, we set the information weight threshold at four, so that when four signals are received, information is regarded as having 'high weight'.

At the beginning, in the first period, traders act as if they were perfectly rational no matter what the signal is — one signal is not strong enough information to give rise to biased confidence. In the second period, if the second signal is of the same sign as the first one, the confidence function K jumps from $K_1=1$ to $K_2=2$, overconfidence appears and the price overreacts to available information. This *delayed overreaction* happens with probability $1/2$. At $t=3$, overconfidence still pervades traders' strategies if another, third signal of

the same sign is observed; thus $K_3=2$ and the price continues to overreact with probability $1/4$ and with probability $3/4$ the confidence function reverts to (or stays at) its default neutral value $K_3=1$. Up until $t=3$, information was of low weight, and overconfidence ensued whenever information reached high strength. In the final trading period $t=4$ however, there are enough signals for investors to consider the available information to exhibit high weight—there will be no overconfidence any more and the maximum possible value for K will be $K_4=1$. Thus if in the fourth period the difference between number of signals of the same sign is less than two, information is regarded as having high weight and low strength. In such a case, the confidence function jumps from $K_3=1$ to $K_4=0.5$ and underconfidence arises. As a result, the price underreacts to a series of (four) signals with probability $3/8$. It is worthwhile to notice also that in case of previous continued overreaction (due to overconfidence), the price is *not* adjusted to its rational level in the fourth period, but merely the response to fourth signal of the same sign is equivalent to a rational expectations response. In the final period, the price is set to its fundamental value.

With all the possible signal sequence realizations, there are two sequences that result in both over- and underconfidence appearing at some time throughout the trading horizon: either two positive signals are followed by two negative ones, or two negative signals are followed by two positive ones. If one of these scenarios is the case, the equilibrium price exhibits delayed overreaction, after which it stays at the overreaction level for one more period; subsequently, the price underreacts to the fourth, final signal, and thus fails to adjust to the rational expectations level.

Let us turn to the analysis of the expected path of confidence function and its influence on equilibrium trading intensities, information transmission, volatility and market depth. We shall compare our results with the corresponding rational outcomes.

As mentioned above, overconfidence and underconfidence pervade the informed traders' demand functions with certain probabilities in different trading periods; we can thus calculate the expected value of the confidence function at all four trading dates. Thus, at $t=1$, $E[K_1]=K_1=1$, $E[K_2]=\frac{24}{16}$, $E[K_3]=\frac{20}{16}$, and $E[K_4]=\frac{13}{16}$. Overconfidence expected at dates $t=2$ and $t=3$ is obviously lower than it would be in case of constant overconfidence—our results will thus differ from constant overconfidence models. The sudden jump to expected overconfidence at $t=2$ is followed by a slight correction in the expectation of confidence function at $t=3$; furthermore, at $t=4$, traders are even more “confused” as the probability of receiving conflicting information increases, resulting in a decrease in investor certainty, or underconfidence. Let us see how this pattern of expected confidence affects equilibrium determination of trading magnitudes of interest. The figures below present the temporal evolution of trading magnitudes for the cases of miscalibrated investors (dotted lines) and rational investors (solid lines). The parameter values are $\tau_{e_k}=0.8$, $\forall k$; $\tau_u=1.2$; $\tau_v=1$.

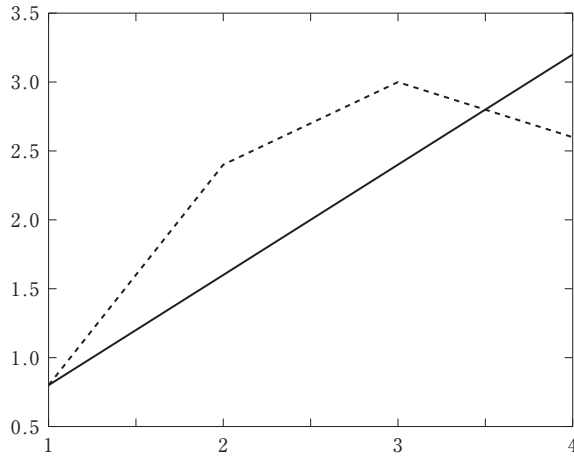


Figure 1: Trading Intensity

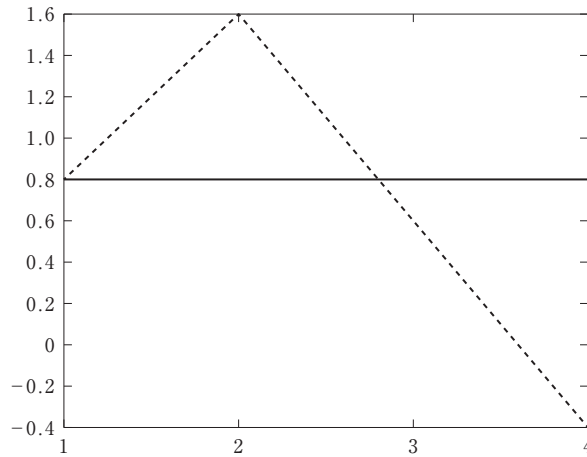


Figure 2: Net Trading Intensity

Trading Intensity

Informed traders subject to biased confidence trade with intensity $a_t = K_t(\sum_{k=1}^t \tau \epsilon_k)$. The net trading intensity, $\Delta a_t = a_t - a_{t-1}$ is also of interest. Overconfident traders trade more aggressively than rational investors in the second and third rounds of trade, but their position turns out to be lower than the corresponding rational one in the final, fourth period. Moreover, it can be seen in Figure 1 and in Figure 2 that irrational investors reverse partly their initial trades.⁴⁾ These trading patterns differ substantially both from the case of rational trading, as well as from trading based on constant overconfidence.

Market Depth

Figure 3 shows the pattern of market liquidity proxy—market depth, which is a reciprocal of the price impact of trade. Absolute market depth at time t is given by $\lambda_t^{-1} = \frac{\tau_t}{\tau_u |\Delta a_t|}$. Two forces affect the expected temporal evolution of liquidity: the net

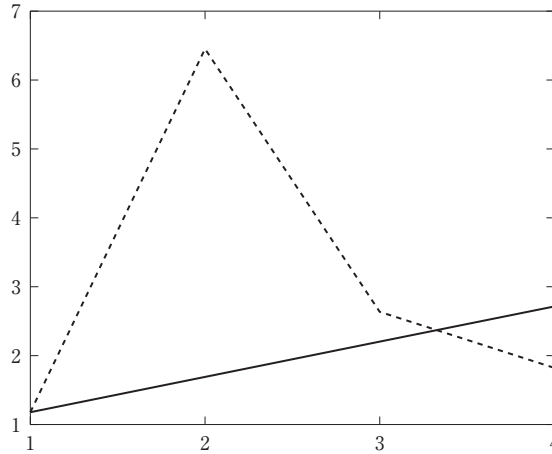


Figure 3: Market Depth

trading intensity Δa_t and the price volatility τ_t . Though initially they comove, later on the increase in price precision is not as great as the differential trading intensity of informed traders, and this second effect dominates, resulting in a decrease in market depth. This nonmonotonic pattern is a result of greater uncertainty on the part of irrational traders in later trading rounds, and is in contrast to the increasing market depth in the case of rational expectations.

Conditional Price Volatility and Price Precision

The precision of prices (depicted in Figure 5), given by $\tau_t = \tau_u + \tau_u \sum_{k=1}^t (\Delta a_k)^2$ affects in turn conditional price volatility (Figure 4) $\text{Var}_t [p_t | p_{t-1}]$, which can be calculated to be equal to $\text{Var}_t [p_t | p_{t-1}] = \frac{1}{\tau_t - 1} - \frac{1}{\tau_t}$. Overconfident investors make the price more informative than in case of rational traders, particularly when overconfidence first appears, i.e. at $t=2$. Subsequent increases in price precisions are much lower, and, in general, also lower than the linear increase in price precision for the case of rational expectations. We have thus shown that, even with multiple signals received throughout the trading horizon, the expected impact on price informativeness may differ if investor confidence is affected by information. Similarly for the case of conditional price volatility, which drops much more sharply in response to “confidence trading” than to rational trading.

While we emphasize that the results above were obtained for only a range of parameter values, we believe they can hold in the general setting. We summarize the above results in the following proposition.

Proposition 1. *If investor confidence is affected by the strength and weight of information, expected trading magnitudes for a range of parameter values display the following patterns:*

- *Informed investors overreact to information initially and trade more aggressively than rational investors, but they reverse partly their position later during the trading horizon.*
- *Market depth is a nonmonotonic, inverted U-shaped curve. In particular, greater uncer-*

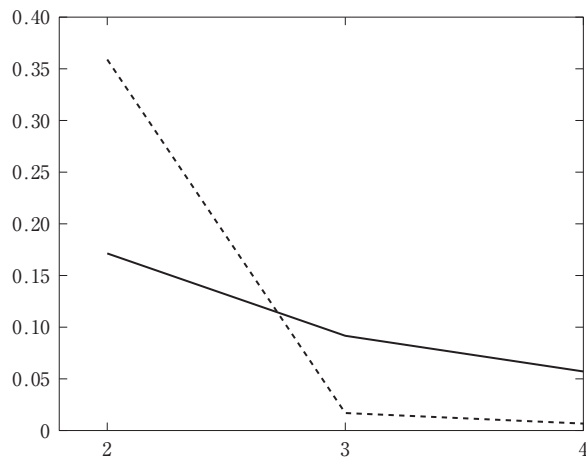


Figure 4: Conditional Price Volatility

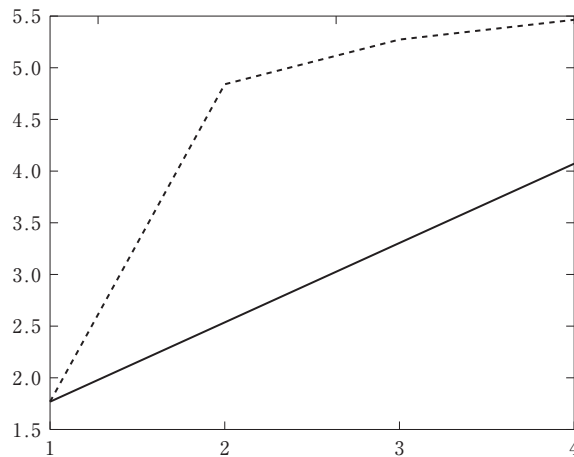


Figure 5: Price Precision

tainty (“confusion”) on the part of irrational traders gives rise to a decrease in the depth of the market with the increase of the amount of information available in the economy.

- *Prices are more informative than in case of rational trading; initial information has greater impact on the price precision and conditional price volatility than late-arriving information.*

5 Discussion

The analyses presented in this paper are consistent with evidence from the cognitive psychology literature. In particular, our assumptions are consistent with both the results of Griffin and Tversky (1992) [12] on the possibility of underconfidence when information is regarded as having high weight, and with those documented by Peterson and Pitz (1988)

[18] on the increase in uncertainty when more information is available. Moreover, we have been able to generate an interesting empirical prediction regarding the overreaction bias in asset prices—overreaction is delayed. This happens in our model because although investors overestimate their information, they are not necessarily overconfident right from the starting point; rather, when a string of signals arrives, people act rationally at first and only after the information generated by the signals has become salient enough, they overreact and become overconfident. Similarly with underreaction and underconfidence—it only matters contingent on the information that appears within the economy. This interplay of (ir)rationality and information has so far received little attention in the literature; while we do not postulate that it is the only right way to go about explaining the behavior in financial markets, it seems to be at least worth investigation as a part of a coherent comprehensive asset pricing theory.

Notice that, in contrast with the existing literature, irrational traders in our models are not always irrational—at the beginning of the trading horizon, there is little information and thus no particular reason for biased behavior, in accordance with the experimental evidence. On the other hand, with enough information already revealed in the economy, it is conceivable to admit that most information is public and there is no more room for irrationality to influence prices. The traders in our setting thus suffer from “*temporal irrationality*”.

The assumptions we impose on the behavior of traders are admittedly rather strong. However, we defend this approach by first noting that the assumptions are in fact consistent with evidence on miscalibration and information presented in the first part of the paper. In particular, biased confidence evolves in our model as a function of information, which lies at the backbone of the economy. This contrasts with the setup in Gervais and Odean (2001) [11], who instead allow investors in their model to update their confidence levels according to feedback from their investment performance. In a way, their biased confidence stems from another bias concerning the evaluation of one’s own performance. It is debatable which approach is more suitable and perhaps a combination of both methods could lead us onto further insights about the influence of biased confidence in asset markets.

Our choice of modeling the confidence function may not be stable to changes in setups. The next step in analyzing the interplay of information and confidence would be arguably endogenizing the confidence function. If we can understand how information affects uncertainty and investor confidence by explaining it as an equilibrium phenomenon, our knowledge of the processes behind numerous issues of importance in financial economics and generally social sciences should be expected to only expand.

6 Concluding Remarks

We have attempted in this paper to introduce biases in confidence resulting from

particular attributes of information into a general financial market setting. Consistent with experimental evidence, we posit that confidence is influenced by the strength and weight of information. Confidence function is introduced as a way of formalizing the relationship between information and confidence. We have shown that if investors' confidence is affected by information strength and information weight, then prices exhibit delayed overreaction to information events; this overreaction may continue for a prolonged period of time. Furthermore, as more and more information is introduced, uncertainty increases among irrational investors and prices tend to underreact to ambiguous news. In another model based on a generalized setting, we have found that depending on the intensity of irrational trading, prices exhibit positive serial correlation when there are few miscalibrated traders in the economy or their bias is moderate; prices overreact to news if the opposite conditions are met.

We view our simple approach as a starting point for a more comprehensive analysis of the interplay between bounded rationality, uncertainty, and information. It is questionable that irrational behavior is built into human decision making processes — rather, it is an outcome of various influences, among which information and its many aspects seem particularly important. Hence, we make a step towards elaborating on Arrow's (1986) [1] assertion that "rationality is not a property of the individual alone"; he further argues that only under very ideal conditions the assumption of rationality is plausible; in complex environments, characterized by composite information structures, the rationality assumptions "become strained and possibly even self-contradictory"⁵⁾. Further research should concentrate on pinpointing the conditions under which rationality ceases to be a credible hypothesis and identifying ensuing consequences for economic variables of interest.

Notes

- 1) Griffin and Tversky (1992) [12], page 422.
- 2) The two examples correspond to information strengths of 50 and 8.8 respectively, which translates to the first case with 3 tosses being roughly 5.7 times stronger information than the second case — see Nelson et. al. (2001) [16], p.175, Table 1.
- 3) See Benos (1998) [2], Odean (1998) [17], or Caballé and Sákovics (2003) [8], among others.
- 4) Trade reversals are also shown to be caused by insider trading in Brunnermeier (2005) [6].
- 5) Arrow (1986) [1], page 385.

References

- [1] Arrow, Kenneth J., 1986, Rationality of Self and Others in an Economic System, *Journal of Business* 59(4), 385-399.
- [2] Benos, Alexandros V., 1998, Aggressiveness and Survival of Overconfident Traders, *Journal of Financial Markets* 1(3-4), 353-383.
- [3] Bernardo, Antonio, and Ivo Welch, 2001, On the Evolution of Overconfidence and Entrepreneurs, *Journal of Economics and Management Strategy* 10(3), 301-330.
- [4] Bloomfield, Robert, Robert Libby, and Mark W. Nelson, 1999, Confidence and the Welfare of Less-Informed Investors, *Accounting, Organizations and Society* 24(8), 623-647.

- [5] Bloomfield, Robert, Robert Libby, and Mark W. Nelson, 2000, Underreactions, Overreactions and Moderated Confidence, *Journal of Financial Markets* 3(2), 113-137.
- [6] Brunnermeier, Markus K., 2005, Information Leakage and Market Efficiency, *Review of Financial Studies* 18(2), 417-457.
- [7] Brzeźniak, Zdzisław, and Tomasz Zastawniak, 1998, *Basic Stochastic Processes*, Springer.
- [8] Caballé, Jordi, and József Sákovics, 2003, Speculating Against an Overconfident Market, *Journal of Financial Markets* 6(2), 199-225.
- [9] Chari, V. V., and Patrick J. Kehoe, 2004, Financial Crises as Herds: Overturning the Critiques, *Journal of Economic Theory* 119(1), 128-150.
- [10] De Long, J. Bradford, Andrei Shleifer, Lawrence Summers, and Robert Waldmann, 1990, Noise Trader Risk in Financial Markets, *Journal of Political Economy* 98(4), 703-738.
- [11] Gervais, Simon, and Terrance Odean, 2001, Learning to be Overconfident, *Review of Financial Studies* 14(1), 1-27.
- [12] Griffin, Dale, and Amos Tversky, 1992, The Weighing of Evidence and the Determinants of Confidence, *Cognitive Psychology* 24(3), 411-435.
- [13] Grinblatt, Mark, and Bing Han, 2002, The Disposition Effect and Momentum, NBER Working Paper <http://papers.nber.org/papers/w8734.pdf>
- [14] Harris, Milton, and Artur Raviv, 1993, Differences of Opinion Make a Horse Race, *Review of Financial Studies* 6(3), 473-506.
- [15] Keynes, John M., 1921, *Treatise on Probability*, MacMillan New York.
- [16] Nelson, Mark W., Robert Bloomfield, Jeffrey W. Hales, and Robert Libby, 2001, The Effect of Information Strength and Weight on Behavior in Financial Markets, *Organizational Behavior and Human Decision Processes* 86(2), 168-196.
- [17] Odean, Terrance, 1998, Volume, Volatility, Price, and Profit When All Traders Are Above Average, *Journal of Finance* 53(6), 1887-1934.
- [18] Peterson, Dane K., and Gordon F. Pitz, 1988, Confidence, Uncertainty, and the Use of Information, *Journal of Experimental Psychology: Learning, Memory, and Cognition* 14(1), 85-92.
- [19] Shiller, Robert, 1981, Do Stock Prices Move too Much to be Justified by Subsequent Changes in Dividends, *American Economic Review* 71(3), 421-436.
- [20] Vives, Xavier, 1995, Short-Term Investment and the Informational Efficiency of the Market, *Review of Financial Studies* 8(1), 125-160.