STAIRS 2014
U. Endriss and J. Leite (Eds.)

doi:10.3233/978-1-61499-421-3-31

Towards modeling surprise in economics and finance: a cognitive science perspective

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Abstract. In financial markets, market participants need to cope with risk and uncertainty, to forecast possible scenarios, and to constantly analyze and revise their beliefs, expectations, and strategies in the light of the massive amount of economical and financial information they receive. Interestingly, the relevance does not seem to reside in the numbers itself but rather whether they elicit "surprise" for market participants. In this paper we review the presence of the term surprise in economics and finance as well as how it is computed. Then, we present how emotions are defined in cognitive science, provide a formal definition of surprise, and describe the surprise process. Additionally, we present some theories regarding how artificial surprise can be computed. In a case study we compare the two different perspectives on surprise, discussing some similarities and differences. Finally, we present some possible applications of the cognitive science perspective.

Keywords. Autonomous agents and multiagent systems, cognitive modeling, multi-agent-based simulation, multidisciplinary topics, social simulation and modeling

1. Introduction

One of the essential tasks in the context of economics and finance is forecasting. Perhaps one of the best contexts to observe the importance of forecasting as well as the effects of a good or bad forecast is the context presented by financial markets, especially stock markets. In a stock market, market participants need to cope with risk and uncertainty [16], by assessing and, ultimately, attributing probabilities to the occurrence of a potentially good or bad/risky/unexpected event. This kind of assessment is essential because a series of strategies depend somewhat on the probability of the occurrence of events that may have an impact on asset prices [22]. Additionally, participants tend to typically trade based on the risk-return trade-off, i.e., lower (higher) levels of risk are generally associated with lower (higher) levels of potential returns.

In this complex and dynamic environment, market participants need to constantly analyze and revise their beliefs, expectations, and strategies in the light of the massive

[1]Davi Baccan is supported by TribeCA ("Trading and investing with behavioral-emotional Cognitive Agents") project, funded by the FEDER through the "Programa Operacional Regional do Centro".

amount of information they receive [29]. Such information includes a wide variety of financial and economic indicators, and data regarding companies. Interestingly, what seems to be relevant for asset behaviour and prices are not the numbers in itself, but actually whether they are lower, equal, or higher than the general beliefs and expectations, the so-called market consensus (e.g., see [2]). Terms such as "lower (higher) than expected" and "beat (miss) the expectation" are indeed commonly employed in the context of stock markets.

In the literature related to economics and finance there are several different theories and hypotheses that try to explain how a stock market works (e.g., [17, 9]). Traditional economic theories, such as the Efficient Market Hypothesis (EMH) (e.g., [9]), relies on the assumption that market participants have stable and well-defined preferences [28]. Additionally, such theories assume that when participants are confronted with decisions that involve risk, they are able to correctly form their probabilistic assessments according to the laws of probability, calculating which of the alternative courses of action maximize their expected utility. Therefore, most of the participants are efficient in reflecting new information accurately [21]. The EMH refers to hypothesis that market prices fully and instantaneously incorporate the information and expectations of all market participants. Last but not least, the EMH assumes that market participants have no cost in acquiring and analyzing information.

However, behavioral economics (e.g., [15]), i.e., the combination of psychology and economics that aims to understand human decision-making under risk as well as how this behaviour matters in economic contexts, have documented extensive experimental evidence that there are deviations from the rational behaviour. Such deviations, known as behavioral biases, are believed to be ubiquitous to humans, and several of them are clearly counterproductive from the economics perspective. Examples of behavioral biases are herding, and overreaction [5] (i.e., the evidence that most people tend to "overreact" to unexpected and dramatic news events).

In this paper we review in Section 2 the presence of the term surprise in economics and finance as well as how it is computed. Then, we present in Section 3 how emotions are defined in cognitive science, provide a formal definition of surprise, and describe the surprise process. Additionally, we present some theories regarding how artificial surprise can be computed. In Section 4 we describe a case study in which we compare the two different perspectives on surprise. In Section 5 we discuss some similarities and differences between the perspectives and point out some possible applications of the cognitive science perspective on artificial surprise.

2. Surprise in economics and finance

In this section we briefly present which investment and trading strategies are used by market participants, show evidence of the presence of the term surprise in the context of economics and finance as well as how it is computed.

2.1. Investment and trading strategies

In the scenario of a stock market there are, generally speaking, three investment or trading strategies commonly used by market participants in creating beliefs, expectations, and goals.

First, technical analysis (also referred to as graphical analysis) (e.g., [8]) make use of a myriad of statistical indicators derived from and build upon stocks data together with graphical patterns and tools to understand stock prices behaviour, identify trends and ultimately to discover and explore profit opportunities. The underlying assumption is that prices incorporate all relevant information, and both past behaviour and returns are rich in information concerning future behavior so that they can be used to some extent to predict or indicate future movements, i.e., history repeats itself.

Second, some market participants, known as “noise traders” [4], do not employ any “rational” mechanism, tend to form incorrect beliefs and expectations as well as base their trading strategies on what they consider to be worth information but actually is simple noise.

Third, fundamental analysis (e.g., [11]), whose rational is more in line with this work, is concerned with the estimation of the intrinsic (also referred to as fundamental or “fair”) price. It begins with the estimation of the intrinsic value of a company, which includes both tangible and intangible assets. This task also involves the analysis of a wide range of factors like the understanding of the current macroeconomics scenario as well as the forecasting of possible scenarios. Additionally, it requires a close examination of financial information regarding the company (e.g., earnings). Finally, fundamental analysis is interested in identifying the internal and external risks which may affect the company. The work of fundamental analysis commonly results in a variety of ratios (e.g., P/E ratio, i.e., price-to-earnings ratio) which are used to estimate whether a current asset price deviates from the “fair” price. The problem relies on the fact that fundamentals are not totally observable. Forecasters often diverge in their opinions and forecasts to that the success of fundamental analysis resides in the estimation accuracy regarding the “fair” price.

2.2. *The term surprise in economics and finance*

There are a series of examples of the presence of the term surprise in the context of finance and economics (e.g., interest rates [12], surprise indexes [27], and overreaction [5]). However, some of the most prominent examples come from the research related to earnings surprise (e.g., [3, 7]). Considering the rational presented by the fundamental analysis, the basic interpretation is that when the actual earnings, released by companies with a given periodicity, are higher (lower) than the expected by the so-called market consensus, market participants should, according to Efficient Market Hypothesis (EMH), react to this new and surprising information accordingly.

The rational regarding earnings surprise can also be applied to other financial and economic indicators of different kinds (e.g., leading economic indicators). Generally speaking, a better than expected data about a relevant indicator (e.g., unemployment rate) may signal that the economy is behaving better than the expected and therefore the earnings of the companies will be also higher than the expected. Some indicators such as the Citigroup Economic Surprise Index (CESI) try to gauge that (see [27] for more details). To illustrate how different indicators relate to each other as well as to stress the importance of earnings/profits for asset behaviour and prices, we show in Figure 1 the evolution of the $S\&P500$, i.e., an index that includes 500 companies in leading industries in the U.S. economy, corporate business profits before tax, and real gross domestic product (GDP).

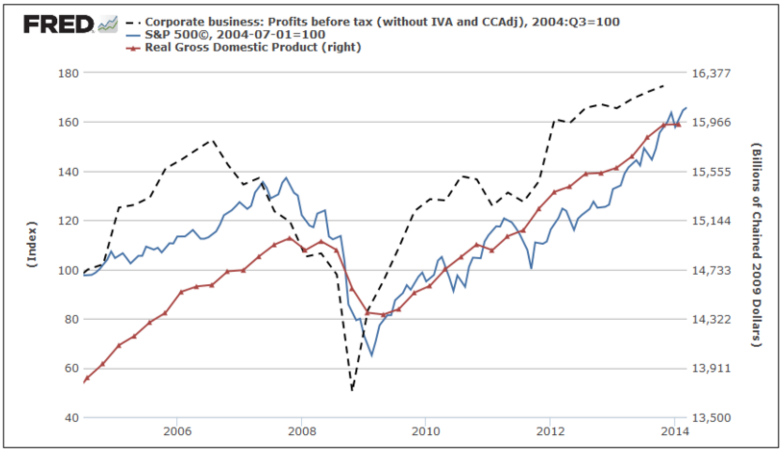

Figure 1. $S\&P500$ index, corporate business profits before tax, and real gross domestic product (GDP), from 01-07-2004 to 01-07-2013, quarterly adjusted, generated with the Economic Research Federal Reserve Bank of St. Louis site - http://research.stlouisfed.org/.

2.3. Market consensus and the computation of surprise

Forecasts with the goal of creating a so-called market consensus are generated by a set of persons such as economists and professionals of financial markets. For instance, traditional economic and financial services periodically surveys groups of economists and professionals on a set of indicators. In this context, there are several different methods for computing earnings surprise (e.g., [14]). The earnings surprise is calculated by performing some kind of comparison between the actual earnings with the consensus estimate (generally the mean or the median of the forecasts).

The basic method for computing the unexpected earnings *(UE_q)* is calculated by dividing the actual earnings *(EPS_q)* by the consensus estimate *(EST_q)* in the time preceding the announcement, e.g., a quarter q: $UE_{q1} = EPS_q/EST_q$ (Equation 1). The unexpected earnings *(UE_q)* can also be calculated by a slightly different method: $UE_{q2} = EPS_q - EST_q$ (Equation 2). Also, there are two different and more sophisticated scaling methods for computing the unexpected earnings. The scaled unexpected earnings *($SCUE_q$)* is calculated by dividing unexpected earnings *(UE_{q2})* by the absolute value of reported eps *(EPS_q)*: $SCUE_q = \frac{UE_{q2}}{abs(EPS_q)}$ (Equation 3). Similarly, the standardized unexpected earnings *(SUE_q)* is calculated by dividing the unexpected earnings *(UE_q)* by the standard deviation of the consensus estimate *($\sigma\ EST_q$)*: $SUE_q = \frac{UE_{q2}}{\sigma EST_q}$ (Equation 4). The same rational used to compute earnings surprise can be applied to compute the surprise "felt" by market participants with respect to other micro and macro economic and financial indicators.

3. Surprise in cognitive science

In this section we briefly present how emotions are defined by cognitive emotion theories. Then, we provide a formal definition of surprise, describe the surprise process, as well as present some theories regarding artificial surprise.

3.1. Cognitive Emotion Theories

Cognitive emotion theories (e.g., [26]), such as the Belief-Desire Theory of Emotions (BDTE) [25], rely on the assumption that emotions are mental states elicited as a result of the evaluation or appraisal of stimuli of all kinds (e.g., events) and can be computed in terms of cognitions (beliefs) and motives (desires). Beliefs are mental states in which one holds a particular proposition to be true, whereas desires represent the motives or future states that one wants to accomplish.

The BDTE [25] is consisted of propositions, beliefs, desires, new beliefs, and two hard-wired comparator mechanisms, namely the Belief-Belief Comparator (BBC) and the Belief-Desire Comparator (BDC). The conceptual framework of the BDTE is the same as the belief-desire theory of action which inspired the BDI (belief-desire-intention) approach to artificial agents. In this section we provide a concise but sufficient description of the BDTE relevant to this work. To understand the nature of both the BDTE and the BDI approach, please see Reisenzein et al. [26].

A proposition p is represented as a tuple $\langle S,B,D\rangle$ where S is the mental language expressing the proposition p, B and D are quantities representing, respectively, the agent's degree of belief and desire regarding proposition p. The strength of a belief in a proposition p at time t, is defined as $b(p,t)$, where $b(p,t) \in \mathbb{R}$ and $0.0 \leq b(p,t) \leq 1.0$, where 1.0 denotes certainty that p, 0.5 maximal uncertainty, and 0.0 certainty that not p. Similarly, the strength of a desire about a proposition p at time t, is defined as $d(p,t)$, where $d(p,t) \in \mathbb{Z}$ and $-100 \leq d(p,t) \leq +100$, where positive values denote desire in favor of p, negative values denote desire against p, and 0 denotes indifference. A new belief is the belief or fact in a proposition that agents receive basically through its sensors (e.g., vision).

The Belief-Belief Comparator (BBC) compares each newly acquired belief with all pre-existing beliefs, looking for match versus mismatch. A match (mismatch) means that a pre-existing belief was confirmed (disconfirmed) by the newly acquired belief. As a result, BBC yields either a belief-confirmation signal or belief-disconfirmation signal. Similarly, the Belief-Desire Comparator (BDC) compares each newly acquired belief with all pre-existing desires, looking for match versus mismatch. A match (mismatch) means that a desire was "fulfilled" ("frustrated"). As a result, BDC yields either a desire-fulfillment signal or desire-frustration signal. BDTE defines emotions as products or signals produced by the BBC and BDC.

For example, suppose an agent has $b(p,t) = 0.9$ and $d(p,t) = +80$, i.e., at time t the agent believes proposition p will happen, and has a desire in favor of p. When the agent receives a new belief at time $t+1$ that actually p not happened, the BBC yields a belief-disconfirmation signal (surprise), since what the agent believed at t as less likely really happened. Similarly, the BDC yields a desire-frustration signal, since the agent has a desire in favor of p.

3.2. Surprise

Surprise is a neutral valence emotion, formally defined as a peculiar state of mind, usually of brief duration, caused by unexpected events, or proximally the detection of a contradiction or conflict between newly acquired and pre-existing beliefs [23, 19]. Surprise serves us in many functions such as attention and learning, being considered, from an evolutionary perspective, crucial for survival in a rapidly changing environment.

Surprise is closely related to how beliefs are stored in memory. Our semantic memory, i.e., our general knowledge and concepts about the world, is assumed to be represented in memory through knowledge structures known as schemas (e.g., [1]). A schema is a well-integrated chunk of knowledge or sets of beliefs, which main source of information available comes from abstraction from repeated personally experienced events or generalizations. Schemas serve the interpretation of present and past, and make it possible the prediction of future events by means of the adaptive guidance of action.

3.2.1. The Surprise Process

Meyer et el. [23] proposed a cognitive-psychoevolutionary model of surprise. They claim surprise-eliciting events elicit a four-step sequence of processes.

The first step is the appraisal of an event as unexpected or schema-discrepant. For instance, in the case of the BDTE, one of the functions of the BBC is the detection of disconfirmation between pre-existing and newly acquired beliefs or, in other words, to detect whether a schema-discrepancy occurs.

If the degree of unexpectedness or schema-discrepancy exceeds a certain threshold then, in the second step, surprise is experienced, ongoing mental process are interrupted and resources such as attention are reallocated towards the unexpected event.

The third step is the analysis and evaluation of the unexpected event. It generally includes a set of subprocesses namely the verification of the schema discrepancy, the analysis of the causes of the unexpected event, the evaluation of the unexpected event's significance for well-being, and the assessment of the event's relevance for ongoing action. It is assumed that some aspects of the analysis concerning the unexpected event are stored as part of the schema for this event so that in the future analysis of similar events can be significantly reduced both in terms of time and cognitive effort.

The fourth step is the schema update. It involves producing the immediate reactions to the unexpected event (if it is the case), and/or operations such as the update, extension, or revision of the schema or sets of beliefs that gave rise to the discrepancy. The schema change (belief update process) ideally enables one to some extent to predict and control future occurrences of the schema-discrepant event and, if possible, to avoid the event if it is negative and uncontrollable, or to ignore the event if it is irrelevant for action.

3.2.2. Artificial Surprise

Two models of artificial surprise for artificial agents can be stressed namely the model proposed by Macedo and Cardoso [20] and the model proposed by Lorini and Castelfranchi [18]. Both models were mainly inspired by the cognitive-psychoevolutionary model of surprise proposed by Meyer et el. and have influence of the analysis of the cognitive causes of surprise from a cognitive science perspective proposed by Ortony and Partridge [24]. To a detailed description of the similarities and differences of the models see [19]. There are other approaches of artificial surprise proposed for other context rather than artificial agents (e.g., [13]). We consider the model proposed by Macedo and Cardoso as the simplest, easy to understand, and straightforward existing model for artificial surprise.

Macedo et el. carried out an empirical study [20] with the goal of investigating how to compute the intensity of surprise in an artificial agent. They proposed several alternative functions for computing the surprise intensity based on the assumption that the surprise "felt" by an agent elicited by an event E_g is proportional to the degree of unexpectedness of the event E_g. They examined the functions by carrying out a two-step experiment. First, they collected ratings of probability and surprise intensity provided by human participants in two domains (political elections and sports games). Second, they empowered artificial agents with the alternative functions as well as with the ratings of probability provided by human participants so that the artificial agents were able to compute the surprise intensity values. Finally, the values obtained by the artificial agents were compared with the actual surprise intensity given by human participants.

This study suggested that the intensity of surprise about an event E_g, from a set of mutually exclusive events E_1, E_2, ..., E_m, is a nonlinear function of the difference, or contrast, between its probability/belief and the probability/belief of the highest expected event (E_h) in the set of mutually exclusive events E_1, E_2, ..., E_m. Formally, let (Ω, A, P) be a probability space where Ω is the sample space (i.e., the set of possible outcomes of the event), $A = A_1, A_2, ..., A_n$, is a $\sigma field$ of subsets of Ω (also called the event space, i.e., all the possible events), and P is a probability measure which assigns a real number $P(F)$ to every member F of the $\sigma field$ A. Let $E = E_1, E_2, ..., E_m$, $E_i \in A$, be a set of mutually exclusive events in that probability space with probabilities $P(E_i) \geq 0$, such that $\sum_{i=1}^{m} P(E_i) = 1$. Let E_h be the highest expected event from E. The intensity of surprise about an event E_g, defined as $S(E_g)$, is calculated as: $S(E_g) = log_2(1 + P(E_h) - P(E_g))$ (Equation 5). In each set of mutually exclusive events, there is always at least one event whose occurrence is unsurprising, namely E_h.

4. Comparing different perspectives on surprise: a case study

We carried out a case study to compare the computation of surprise from the perspective of economics and finance to the perspective of cognitive science. We obtained the free data related to the forecasts from the Wall Street Journal (WSJ) (http://projects.wsj.com/econforecast/). The WSJ monthly surveys a group of nearly 50 economists on more than 10 major economic indicators. For this case study we selected the unemployment rate as indicator as well as compiled its data from 01-07-2008 to 01-01-2014 in a total of 70 months. Similarly, we obtained the actual/released data regarding the selected economic indicator from the Economic Research Federal Reserve Bank of St. Louis (http://research.stlouisfed.org/).

The economical and financial approach is straightforward. We applied the earnings surprise rational to compute the surprise regarding the unemployment rate (UR). We computed the mean and the standard deviation σEST_m of the forecasts, where $_m$ refers to the monthly periodicity, the unexpected unemployment rate by UUR_m (Equation 1) and UUR_m (Equation 2), the scaled unexpected unemployment rate $SCUUR_m$ (Equation 3) and the standardized unexpected unemployment rate $SUURE_m$ (Equation 4).

The results of this case study are shown in Figure 2.

5. Discussion and conclusion

First of all, it is important to bear in mind that our goal is not to provide evidence neither in favor of nor against the use of a given indicator. We could have selected another indicator(s) without any impact on our results.

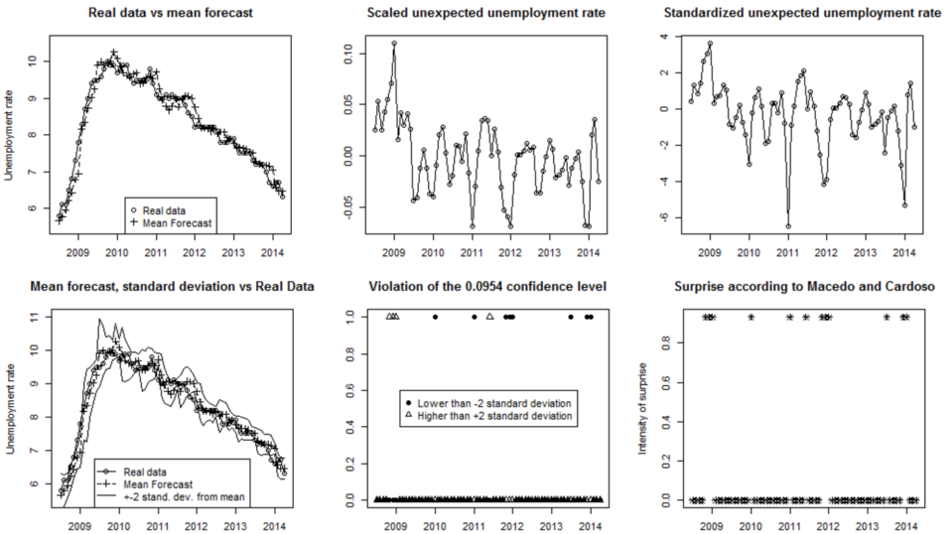

Figure 2. Top: Real data vs mean forecast (left), $SCUUR_m$ (Equation 3) (center), (Equation 4), $SUURE_m$ (Equation 4) (right); Bottom: Mean forecast, standard deviation vs real data (left), Violation of confidence level (center), $S(E_g)$ (Equation 5) (right).

The cognitive science perspective rely on the subjective probabilities to compute artificial surprise (Equation 5). As it should be, considering the underlying theory, it does not capture whether it is positive or negative. Additionally, the higher the difference between the outcomes, the higher may be the surprise.

The economical and financial perspective can be thought of as a pure mathematical approach. It uses a standard deviation to try to capture whether forecasters diverge or converge as well as to present whether the surprise is positive or negative, however, it requires an understanding of the related indicator (e.g., a lower than expected data in unemployment rate is a good thing).

Unlike the straightforward economical and financial perspective, the cognitive science perspective requires the creation of the outcomes and the estimation of its subjective probabilities. For instance, in this work we rely on the assumption that forecasts follow a Normal distribution pattern. We could have used a normality test (e.g., Shapiro Wilk test) or analyzed other variables (e.g., kurtosis) to test that assumption. However, the results may be true for one group and false for another group (the efforts spent on such task would be probably in vain). Nevertheless, we consider that relying on this assumption does not have any impact on our results, especially taking into account that we used this rational just to create the so-called consensus. Despite that, one should indeed be careful in assuming the Normal distribution pattern in other contexts (e.g., there is substantial evidence that financial asset returns are not normally distributed [16]). Other methods would ideally include mechanisms such as self-reports so that forecasters should be able to express their confidence in their forecasts. With this information one may be able to weight the forecasts more precisely. Another approach may include the analysis of different financial instruments (e.g., options) to try to infer the beliefs of market participants by observing their actions.

Considering the cognitive science perspective, what we are able to say is that the release of an indicator may elicit surprise only on a given set of persons, the so-called market consensus and not the entire market. Instead of carrying meaningful information, terms such as "beat (miss) market expectation" seem to carry just "noise" and, in the end, does not seem to make much sense, at least from this perspective.

The findings of the behavioral economics together with empirical observations of the behaviour of market participants have been stressing the necessity of adopting novel approaches [10] in order to improve our understanding of complex economical and financial systems [6]. One of the possible ideas is the use of cognitive modeling approaches. Having cognitive agents means that artificial agents will be empowered with mechanisms similar to or inspired in those used by humans. Therefore, the behaviour of artificial agents tends to be closer to the behaviour of humans in a similar scenario. Our multidisciplinary work is line with this context. It is, as far as we know, one of the first attempts (possibly the first) to bring together two different approaches on surprise, by presenting and describing what surprise is from the cognitive science perspective and, furthermore, how an artificial surprise model can be computed and applied to economics and finance. The use of cognitive modeling approaches in this kind of complex systems is in its early stages. We consider that the use of relatively simple but powerful tools in conjunction with other cognitive models, like those discussed in this work, offers a rich and novel set of possibilities for investigation and to shed light on the behaviour of cognitive agents.

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