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SCIENCE DIRECT®
Information Sciences 170 (2005) 121–131
INFORMATION SCIENCES
AN INTERNATIONAL JOURNAL
www.elsevier.com/locate/ins

Computational intelligence in economics and finance: Carrying on the legacy of Herbert Simon

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Abstract

This is an editorial guide for the special issue on computational intelligence (CI) in economics and finance. A historical introduction to the background is given. This research paradigm is traced back to Herbert Simon, who, as a founder of artificial intelligence, pioneered the applications of AI to economics. The move from the classical AI to CI indicates a continuation of the legacy of Herbert Simon. Computational intelligence has proved to be a constructive foundation for economics. In responding to what Herbert Simon referred as procedural rationality, our study of bounded rationality has been enriched by bringing autonomous agents into the economic analysis.

Keywords: Computational intelligence; Artificial intelligence; Agent-based computational economics; Autonomous agents; Stock price-volume relation; Micro-macro relation

1. Computational intelligence in economics and finance

The incessant interaction between the development of real-world issues and the progress in science has continuously moved the frontier of economics

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doi:10.1016/j.ins.2003.11.006

forward. Herbert Simon, as the only person to win the *Nobel Memorial Prize in Economics, the Turing Award* by the ACM and the ORSA/TIMS von Neumann Prize, is a perfect illustration of this advancement in economics. Being a lifelong scholar of *human decision-making*, Simon believed that economic research should start from the study of actual behavior rather than be based on convenient but unrealistic assumptions. He acted upon his belief by drawing materials from his own contributions to *computer science* and *cognitive psychology* so as to enrich the study of economics and management science. His inventions in economics, *satisfying behavior* and *bounded rationality*, were substantiated by making extensive use of the computer to simulate human thinking and to augment it with *artificial intelligence*.

The development of economics over the last two decades has been largely in line with the legacy of Herbert Simon. Artificial intelligence, of which Simon was one of the founders, is now widely applied to modeling the adaptive and learning behavior of boundedly-rational agents. With the advent of the high-performance computing era, computer simulations of human behavior, on which Simon spent more than 40 years, seem to have become a promising direction for empirically grounded economic reason. The significance of psychological and behavioral approaches to economics, of which Simon was a pioneer, was well acknowledged by the Nobel Prize Committee. [1]

Simon's main contribution to AI is what is known as the *symbol-processing approach*, a kind of classical AI. There is a severe limitation of this approach. Where do the symbolic concepts come from? How do they evolve and grow? How are they modled by feedback from the environment? Symbol-processing computers (agents) cannot come up with useful ideas of their own to make sense of new situations. Since the economic system is doubtlessly a complex adaptive system, in which surprises, innovations, novelties, and sudden changes are ubiquitous, it is hard to satisfy modeling agents living in such a system with just a manually-driven device. Over the last decade, an interdisciplinary research area, known as *autonomous agents*, has opened a new avenue to economists who are longing for the *life* of economic agents in their models. [2]

The implementation of autonomous agents in economic models was made feasible or easier by a series of toolkits from the development of modern AI. Collectively, they are known as *computational intelligence* (CI). It has been shown in many different contexts how CI has effectively extended Simon's boundedly-rational agents into autonomous agents. Little by little, CI has been

[1] Mentioning this is particularly appropriate when the 2002 Nobel Laureates in economics just happen to be pioneers of these two fields of research: Daniel Kahneman and Vernon Smith.

[2] The idea that agents possess *artificial life* was first introduced to economists in [30]. Also see [8] for a historical development of the idea of *adaptive economic agents* in the light of genetic algorithms and genetic programming.

written into the economic journals, monographs, edited volumes and even textbooks. [3] What did not take place was an international meeting to enable CI economists or finance people to meet face-to-face to exchange interesting ideas. The only conference to come close to this idea was the *IEEE Conference on Computational Intelligence for Financial Engineering* (CIFEr). Nonetheless, CIFEr was exclusively devoted to financial engineering, which left behind many other major economic applications of CI, such as macroeconomic and game-theoretic modeling.

In 1998, the tenth international conference on *Tools with Artificial Intelligence* was held in Taipei. I was invited to chair a session where economic applications of AI were presented. On that occasion, Prof. Paul Wang's work on applying artificial intelligence to economics was known to me. Since, among a large group of computer scientists, we were the only ones who shared Herbert Simon's vision of economics, a conversation between us naturally extended beyond the closing of the conference. During this protracted conversation, a number of fascinating ideas were generated. The top priority was to organize a conference which was entirely devoted to the economic and financial applications of computational intelligence. At that time, the *joint conference on information sciences* (JCIS) had already been run for many years, but there was no single track with a focus on economics and finance, and the list of information sciences was deemed to be far from complete if a subject like economics were found to be absent. [4] Prof. Wang, therefore, encouraged me to organize such an event for the JCIS, and to materialize the rich content of the information sciences. The *first international workshop on computational intelligence in economics and finance* (CIEF), as a part of JCIS, was then held in Atlantic City on February 27 to March 3, 2000.

While all kinds of economic and financial applications were solicited by this workshop, particular emphasis was placed on the two major areas of application, namely, *financial data mining* and *agent-based computational modeling of economics and games*. The first theme put the test of different types of learning behavior within a really challenging arena, i.e. data from financial markets, which constituted one kind of complex adaptive system, whereas the second theme led us directly to the complex adaptive systems themselves.

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[3] A nice review of CI written to economists can be found in [14]. To impress those who are unfamiliar with this area, the following is just a glossary of the published books: [1–5,9,10,15,17–19,22–26,29,32–34,36,37].

[4] It has been over a long period of time that economists have made the role of information explicit in their economic analysis. In econometrics, the maximum entropy principle based on the Shannon information theory and the minimum description length principle based on the algorithmic information theory have been applied to model selection. A course entitled *economics of uncertainty and information* is now offered in many graduate schools of economics. See [7] for a review of information theory in economics.

Simon, in his lifetime study, had a broader interest than just the computer simulation of agents' learning behavior. His repercussion to John Holland's work on complex adaptive systems is also included in the last two chapters of the third edition of his book "*The Sciences of the Artificial*". We hoped that the themes developed in this conference would become a way of carrying on the legacy of Herbert Simon in economics.

Of 33 papers, 27 were accepted by the conference. After the conference, 11 out of the 27 papers were asked to be resubmitted. After two referral and revision processes, each with two or three referees, 6 were rejected. Some of these rejections will be published in our edited Springer volume *Computational Intelligence in Economics and Finance* ([13]). The five that were able to survive to the end will, therefore, be published in the special issue of this journal.

2. Article synopsis

Altogether these five accepted papers address three active application areas of computational intelligence, namely, *financial engineering, artificial stock markets* and *games*. The leading article by Giuliano Armano, Michele Marchesi and Andrea Murru is an application of CI to financial engineering, or more specifically, to financial time series forecasting. The authors propose *local approximation* based on a novel technique of domain decomposition. Their contribution is motivated by a theoretical consideration, i.e. *multi-stationarity* in a financial time series, or using a different term, *piecewise stationarity* or *quasi-stationarity*. The philosophy of the authors is that, under the hypothesis that financial time series are multi-stationary, obtaining a single model that holds for different regimes can be extremely difficult. Therefore, instead of identifying a global model, they attempt to identify different local models, known as the *context-based identification of multi-stationarity* or *guarded experts framework*, an idea that has long been pursued throughout the history of machine learning.

One recent research trend in the financial application of CI has been not to treat the each tool *individually* as if they work alone or compete with each other. Instead, it has been proved that these tools can be more productive if they work *synergetically* together as a team. Armano, et al.'s paper provides an illustration of the use of *hybrid systems*. Their guarded experts system integrates three major CI tools, namely, the extended classifier systems, genetic algorithms, and artificial neural networks. As to the division of labour, the extended classifier plays the role of guarded experts, artificial neural networks are used for implementing predictors, and finally genetic algorithms are used to generate new classifiers. When applying this hybrid system to trading, the authors show its superior performance relative to the buy-and-hold strategy.

The next three papers contribute to different aspects of *agent-based artificial financial markets*. The agent-based artificial financial market, as a main branch of *agent-based computational economics*, is one of the areas where computational intelligence is actively involved. [5] In 1988, when John Holland and Brian Arthur established an economics program at the Santa Fe Institute, the artificial stock market was chosen as the initial research project. Agent-based artificial stock markets have two main stays: *agent engineering* and *institution (trading mechanism) designs*. The former is mainly concerned with *the construction of the financial agents*. In the past a number of CI techniques were applied to the construction of financial agents. [28] showed how to use *genetic algorithms* to encode the trading strategies of traders. A *genetic fuzzy* approach to modeling trader's behavior was shown in [27], whereas the *genetic neural* approach was adopted in [21]. In [6] and [35], we see a perfect example of bringing different learning schemes into the model. The learning schemes incorporated into [6] include an empirical Bayesian trader, a momentum trader, and a nearest-neighbor trader, while those included in [35] are *neural networks* traders and momentum traders. [20] provides a more thorough and general discussion of the construction of artificial financial agents.

What comes with these extensive applications of CI tools to financial agent engineering is the increasing concern with the *foundation* of using these tools to represent *sensible* human adaptive behavior. The paper by Kiyoshi Izumi, Shigeo Nakamura, and Kazuhiro Ueda pioneers a research direction for financial agent engineering. They ground the agent engineering in a *field study* of real investors' behavior. Strange as it may seen, the field study is neglected in most ACE studies despite its great potential for ACE modeling. As to the question frequently asked in the literature, i.e., *whether or not genetic algorithms can represent a sensible learning process of humans*, the authors give a positive answer based on the findings from their field study, which included interviews and questionnaires.

Conventionally, researchers of agent-based artificial financial markets have cared more about the emergent macro phenomena than the micro-structure of their simulations. While those early efforts enhance our understanding of the stylized features well documented in financial econometrics, such as fat tails, volatility clusters, and non-linear dependence, the patterns which one may observe from the micro-structure are basically unexploited. However, in their paper, Izumi, et al. attempt to compare the *micro-structure* observed from their artificial-market simulation with that from the survey data. To do so, they even

[5] A detailed account of the rise and significance of agent-based computational economics can be found in [31]. Prof. Leigh Tesfastion also delivered a keynote speech with the title "*Agent-Based Computational Economics: Growing Economies from the Bottom Up*" as the keynote speaker at the CIEF'2002 workshop.

introduce factor analysis as a tool to effectively summarize the dynamics of agents' perception. While the work is by no means mature, it is certainly an important step toward uncovering the veil of the rich micro-structure of agent-based financial markets.

While agent-based computational economic models are composed of a large number of *software agents*, be they exogenously specified or endogenously generated, the early development of ACE was actually heavily influenced by experimental economics, which consisted mainly of markets or games composed of real *human agents*. One mission of ACE in those early days was to explain the interaction of human agents observed from laboratory experiments through the computer simulation of the interaction of software agents in artificial markets. [6] Although the *society of software* agents can be compared to or related to the *society of human agents* in many insightful ways, the integration of the two may be an even more interesting and challenging task. Koichi Kurumatani, Takahito Yamamoto, Hidenori Kawamura, and Azuma Ohuchi's paper gives a taste of this kind of integration even though it is still in its ealry stages.

In their paper, a platform, referred as to *X-Economy*, provides communication among different types of agents, including both software agents and human agents. The artificial stock market built upon the X-Economy is, therefore, a generalization of the SFI (Santa Fe Institute) artificial stock markets. It now allows both software traders and human traders to compete with each other in the same market and at the same moment in time. In the literature, it has just started to be realized that the introduction of software agents may affect the behavior of human agents. More research in this direction is needed before we can have a full understanding of human–machine interaction in the context of economics.

Like Izumi et al., Kurumatani, et al. also address the micro-structure of their artificial stock markets. However, their difference is clear. The former focuses on the *learning dynamics* of a population of evolving software traders, whereas the latter is interested in the *trading performance* of user-specified software agents. To the best of our knowledge, this is the first publication on using agent-based simulation to examine the performance of trading strategies. While their finding regarding the robustness of the MA (moving average) strategy is still premature, it is not difficult to see how a robustness check can be more rigorously conducted in an agent-based artificial financial market. We believe that this is the future of financial engineering.

At this point, we must point out that the current studies on agent-based artificial financial markets place too much emphasis on the learning dynamics. To be sure, it is still important to know how agents' learning behavior will

[6] See [11] for a list of examples.

affect the market's performance, and it remains to be seen how the heterogeneity of beliefs changes over time. Nonetheless, the difficulty in tracing and explaining what we have has already downgraded the usually claimed "*rich behavior*" to just "*noise*". Tracing and analysis tend to become even more difficult when evolutionary force is added. Therefore, it seems to be equally important to construct agent-based financial markets that are simply based on what is already known to us, and then to test their robustness. Later on, we may introduce the evolutionary dynamics after the basic picture is well grasped. It is from this re-balancing viewpoint Kurimatani, et al.'s contribution is seen.

The previous two papers (Izumi, et al. and Kurumatani, et al.) exhibit an essential feature of ACE: one can perform *a survival analysis (a survival test)* of different kinds of economic behavior, strategies, and theories by using ACE. For example, Izumi's *AGEDASI TOF* helps us to see which economic variables are *considered* to be the most important among market participants in terms of forecasting exchange rates, and how these key variables may change from time to time. Thus, the trade deficit may be a key variable used by most dealers today, but not necessarily tomorrow. This phenomenon of change or instability is very familiar to economists. However, economic changes, instability or nonstationarity has long been studied by economists, especially econometricians, in the context of aggregate dynamics (macroeconomic dynamics). Using aggregate data, they build an associated functional relation, and then estimate and test it using the standard statistics. From this procedure, we can say something about the aggregate relation, including the identification of change. However, a main problem with this equation-based approach is its lack of a *micro-foundation*.

For example, suppose that we find from our aggregate data that the trade deficit is no longer important in forecasting exchange rates. Will that necessarily imply that most market participants have already given up the use of it? On the other hand, if from our survey data most market participants do not consider the trade deficit to be important, does that automatically mean that it must be the case that the trade deficit will be statistically insignificant in our regression model? Briefly, *is the micro-relation necessarily consistent with the macro-relation?* Issues of this sort have been well recognized by economists, as Delli Gatti et al. [16] states:

> Also, the standard econometric tools are based upon the assumption of a representative agent. But if the economic system is populated by heterogeneous agents, the microfoundations of macroeconometrics should be redefined, since some standard procedures (e.g., cointegration, Granger-causality, impulse response functions of structural VARs) loose their significance (Forni and Lippi, 1997). All in all, we may say that macroeconomics (and macroeconometrics) still lack sound microfoundations.

This brief but powerful critique of the mainstream macroeconomics, in particular macroeconometrics, is best illustrated in Shu-Heng Chen and Chung-Chih Liao's paper. This paper studies the *price-volume relation*, which is a hotly-debated phenomenon regarding the stock market. Basically, it is concerned with whether volume can help predict price. Needless to say, econometric techniques have been deeply involved in this issue. Among them, tests based on *Granger causality*, be it linear or non-linear, are the most sophisticated ways used to deal with this problem. In this paper, Chen and Liao apply Granger causality to test whether volume Granger causes stock returns by following what the conventional econometric literature did. The difference is that the test is not based on the real financial data, but on the artificial data generated from their agent-based artificial stock market, the AIE-ASM.

In the AIE-ASM, agents form their expectations of the future return based on the historical data, which includes trading volume. Despite its availability, traders may not necessarily consider trading volume to be useful in forecasting returns. Whether or not they would use trading volume in forecasting returns is determined endogenously via a co-evolutionary process mainly driven by *genetic programming*. This agent-based set-up makes us able to see, individual by individual and day by day, whether or not trading volume is important. They actually count how many surviving agents there are who believe that trading volume would help forecast stock prices. They then compare these number of agents with the Granger causality test results. What turns out to be interesting is that the price-volume relation observed at the macro level (based on the Granger causality test) can emerge from a market where no one actually used volume in their forecasts of returns (based on the survival counts). Based on this inconsistency, they claim, "econometric analysis which fails to take into account this complex feedback relation between the micro and macro aspects may produce misleading results. Unfortunately, we are afraid that this is exactly what mainstream financial econometrics ended up doing in a large number of empirical studies."

Among all of the agent-based models in the social sciences, the *iterated prisoners' dilemma* (IPD) game is probably the one with the longest history. It dates back to 1987 when Robert Axelrod published his pioneering work on using genetic algorithms to simulate IPD games. Based on a very recent survey by [12], the number of publications on the applications of evolutionary computation to IPD games ranks very high with a count of 28. Even though more than a decade has passed, this area is still very active today. It would then be interesting to inquire what makes IPD so attractive. What can make this seemingly quite simple issue so deep and rich? From the paper by Floortje Alkemade, David van Bragt, and Han La Poutré, one may see that it is the great variety of CI that enables us to track the richness and depth of the issue, which may otherwise be hidden under the conventional analytical approach.

Their paper addresses the significance of the *tagging mechanism* in the formation of stable cooperative societies. Nonetheless, what makes this paper unique is a series of efforts to identify the significance of many *options* associated with the use of evolutionary algorithms (EAs). EAs are famous for their great number of options, and because of that researchers need to be careful as to how sensitive their conclusions are to their specific set-ups. This paper provides a very good example of this style of sensitivity analysis. The authors show the contribution of the crossover operator in forming stable societies of cooperating agents. They also show the impact of different crossover styles in achieving cooperation.

Alkemade, et al.'s paper is not just a contribution to IPD games. As a paper in this special volume on CI, it is also rich in technical background. The technical foundation of agent-based modeling, *object-oriented programming*, is introduced explicitly in the paper through *Swarm*, one of the most popular languages in agent-based modeling.

3. Concluding remarks

Like all editors of a special issue of a prestigious journal, it is hoped that through this golden opportunities to gather together several interrelated papers, which may otherwise appear in different and seemingly unrelated places, we can contribute something valuable both loudly and clearly to the academic community. The essence of this special issue is to give a general picture of the research directions which may form the future of this research area. While an attempt to comprehensively address how computational intelligence may enhance the progress of economics and finance is beyond the scope of this issue, the five papers included in this special volume do indicate what we can expect to see more of in the near future.

Computational intelligence has proven itself to be a *constructive foundation* for economics. In responding to what Herbert Simon referred to as *procedural rationality*, our study of bounded rationality has been enriched by bringing autonomous agents into the economic analysis. While it may be a little premature to say whether the idea of autonomous agents has made a profound contribution to the progress of economics, as long as the research trend of agent-based computational economics prevails, CI will continue to play a non-negligible role in economics. Agent based computational economics can partially benefit from the intensive use of CI in financial data mining, as illustrated by the use of genetic neural systems in Armano, et al.'s paper. However, it may benefit more from its collaboration with field studies, experimental economics, behaviorial economics, and econometrics, as Izumi, et al.'s, Kurumatani, et al's, and Chen and Liao's papers exemplify. Finally, the rich expression of CI toolkits enables us to explore the great complexity of an issue, in particular, to understand and cope with its highly controversial nature, as was done in the Alkemade et al.'s paper.

As in all refereed journals, the painstaking efforts made by the referees is indispensable for enhancing the quality of journal. There is a list of people to which we would like to extend our most sincere thanks, including Koen Bertels, John Bower, Herbert Dawid, Torsten Eymann, Herbert Gintis, Giulia Iori, Mak Kaboudan, Christian Keber, Yao Chin Lin, Thomas Lux, Michael North, Thomas Riechmann, Bryan Routledge, Sorin Solomon, Von-Wun Soo, Sylvia Staudinger, Kwok Yip Szeto, George Szpiro, Kay Chen Tay, Elpida Tzafestas, Nick Vriend, and Hsiao-Cheng Yu.

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