On Complex Economic Dynamics: Agent-Based Computational Modeling and Beyond

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Abstract This chapter provides a selective overview of the recent progress in the study of complex adaptive systems. A large part of the review is attributed to agent-based computational economics (ACE). In this chapter, we review the frontier of ACE in light of three issues that have long been grappled with, namely financial markets, market processes, and macroeconomics. Regarding financial markets, we show how the research focus has shifted from trading strategies to trading institutions, and from human traders to robot traders; as to market processes, we empathetically point out the role of learning, information, and social networks in shaping market (trading) processes; finally, in relation to macroeconomics, we demonstrate how the competition among firms in innovation can affect the growth pattern. A minor part of the review is attributed to the recent econometric computing, and methodology-related developments which are pertinent to the study of complex adaptive systems.

Keywords Financial markets · Complexity thinking · Agent-based computational economics · Trading institutions · Market processes

This book is the post-conference publication for *the 21st International Conference on Computing in Economics and Finance* (**CEF 2015**) held on June 20–22, 2015 in Taipei. Despite being the largest conference on computational economics for two decades, CEF has never produced any book volume that documents the path-breaking and exciting developments made in any of its single annual events.

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For many years, the post-conference publications had always been in the form of journals' special issues, which, unfortunately, have ceased to continue in recent years. Consequently, although the voices of CEF had been loud and clear for many years on many prominent issues, they may have been forgotten as time goes by. Without proper archives, it will be difficult for the new-comers to trace the important contributions that the conferences have made in the field of computational economics.

Two years ago, Springer launched a new series, *Springer Proceedings in Complexity*, to publish proceedings from scholarly meetings on topics related to the interdisciplinary studies of the science of complex systems. The scope of CEF fits the mission of this series perfectly well. Not only does CEF deal with problems which are sufficiently complex to defy an analytical solution from Newtonian Microeconomics [9], but CEF methods also treat economics as a science of complex systems, which requires complexity thinking both in terms of ontology and epistemology [22]. Therefore, when Christopher Coughlin, the publishing editor of the series, invited us contribute a volume, we considered it to be a golden opportunity to archive the works presented at CEF 2015, in a way similar to what we had done previously in the form of journals' special issues.

However, CEF 2015 had a total of 312 presentations, which covered many aspects of CEF. To include all of them in a single volume is doubtlessly impossible. A more practical alternative would be to select an inclusive and involving theme, which can present a sharp focus that is neither too narrow nor too shallow. It is because of this consideration that we have chosen one of the most active areas of CEF, namely *agent-based computational economics (ACE)*, as the main theme of this book and have included ten chapters which contribute to this topic. These ten chapters are further divided into three distinct but related categories: *financial markets*, *market processes* and the *macroeconomy*. Although there are other areas of ACE that have also made important advances, we believe that without tracking the development of these three research areas, the view of ACE will become partial or fragmented. These ten chapters, constituting the first part of the book, will be briefly reviewed in Sect. 1.

In addition to these ten chapters, we include three chapters that present new methodologies and technologies to study the complex economic dynamics. Three chapters are contributions of this kind. The first one is an econometric contribution to the identification of the existence and the extent of financial integration. The second one addresses the role of supercomputers in developing large-scale agent-based models. The last one challenges the capability of formal reasoning in modeling economic and financial uncertainties. It also advocates a reform of the economic methodology of modeling the real-world economy. These three chapters, constituting the second part of the book, will be briefly reviewed in Sect. 2.

1 Agent-Based Computational Economics

One core issue that ACE seeks to address in economics is how well the real economy performs when it is composed of heterogeneous and, to some extent, boundedly rational and highly social agents. In fact, a large body of published ACE works can be connected to this thread. This issue is of particular importance when students of economics are nowadays still largely trained under Newtonian economics using the device of a representative agent who is assumed to be fully rational in seeking to maximize a utility function. As an alternative research paradigm to the mainstream, ACE attempts to see how our understanding of the economy can become different or remain the same when these simplifications are removed.

Part of ACE was originated by a group of researchers, including Brian Arthur, John Holland, Blake LeBaron, Richard Palmer, and Paul Tayler, who developed an agent-based model called the Santa Fe Artificial Stock Market to study financial markets [1, 5]. Quite interestingly, their original focus was not so much on the financial market per se, i.e., the financial market as an institutional parameter, but on the exploration of trading strategies under evolutionary learning, the co-evolution of trading strategies and the emergence of market price dynamics. This focus drove the early ACE research away from the role of trading mechanisms and institutional arrangements in the financial markets, which was later found to be a substantially important subject in computational economics and finance. Section 1.1 will summarize the three ACE works that focus on trading institutions, rather than trading strategies.

Market process theory investigates how a market moves toward a state of general economic equilibrium and how production and consumption become coordinated. Agent-based modeling is a modern tool used to analyze the ideas associated with a theoretical market process. In Sect. 1.2, we will give an overview of six works that investigate the price discovery process, market dynamics under individual, and social learning and market herding behaviors using agent-based simulation.

Macroeconomics studies the performance, structure, behavior, and decision-making of an economy as a whole. ACE is a modern methodology that is applied to examine the macroeconomy. In Sect. 1.3, we introduce the work using ACE models to analyze the macroeconomic dynamics under product innovation.

1.1 Financial Markets

Dark Pools is an alternative trading institution to the regular exchanges that have gained popularity in recent years. In dark pools trading, there is no order book visible to the public; hence the intention of trading is not known until the order is executed. This provides some advantages for the institutional traders who can obtain a better realized price than would be the case if the sale were executed on a regular exchange. However, there are also disadvantages in that the order may not be executed because of the lack of information for the order's counter parties. With the growing usage of dark pools trading, concerns have been raised about its impact on the market quality. In the chapter, entitled "Dark Pool Usage and Equity Market Volatility," Yibing Xiong, Takashi Yamada, and Takao Terano develop a continuous double-auction artificial stock market that has many real-world market features. Using various institutional parametric setups, they conduct market simulations to investigate the market's stability under dark pools trading.

The institutional-level parameters that they investigated are:

- Dark pool usage probability (0, 0.2 or 0.4);
- Market-order proportion (0.3–0.8);
- Dark pool cross-probability (0.1–1.0), which is the probability that the buy orders and sell orders in the dark pool are being crossed at the mid-price of the exchange. A lower cross-probability indicates a relatively longer order execution delay in the dark pool.

Their simulation results indicated that the use of mid-price dark pools decreases market volatility, which makes sense because the transaction is not visible to the public until the order is completed. The transactional impact on the market stock prices is therefore minimized. Moreover, they found that the volatility-suppressing effect is stronger when the dark pool usage is higher and when the market-order proportion submitted to the dark pool is lower.[1] They also reported that the dark pool cross-probability did not have any effects on the market volatility.

Another trend in recent financial markets is the use of computer algorithms to perform *high frequency trading (HFT)*. Since computer programs can execute trades much faster than humans, stocks and other instruments exhibit rapid price fluctuations (fractures) over sub-second time intervals. One infamous example is the *flash crash* on May 6, 2010 when the Dow Jones Industrial Average (DJIA) plunged by around 7% (US$1 trillion) in 5 min, before recovering most of the fall over the following 20 min. To understand the impact of HFT on financial markets, in the chapter, entitled "Modelling Complex Financial Markets Using Real-Time Human-Agent Trading Experiments," John Cartlidge and Dave Cliff used a real-time financial-market simulator (OpEx) to conduct economic trading experiments between humans and automated trading algorithms (robots).

The institutional-level parameters that they investigated included:

- Robots' trading speed, which is controlled by the sleep-wake cycle (t_s) of robots. After each decision (buy, sell, or do nothing) is made, a robot will sleep for t_s milliseconds before waking up to make the next decision. The smaller that t_s is, the faster the robots' trading speed and the higher their trading frequency.
- Cyclical vs. random markets: In each experiment, there are six pre-generated assignment permits, each of which contains a permit number and a limit price—the maximum value at which to buy, or the minimum value at which to sell.

[1] See [16] for similar findings using empirical data.

The lower the permit number is, the farther away the limit price is from the equilibrium. In a cyclical market, the permits are issued to humans and robots following the permit numbers. By contrast, the permits are issued in random order in a random market.

Their simulation results showed that, under all robot and human market setups, *robots outperform humans consistently*. In addition, faster robot agents can reduce market efficiency and this can lead to market fragmentation, where humans trade with humans and robots trade with robots more than would be expected by chance. In terms of market type, the cyclical markets gave very different results from those of random markets. Since the demand and supply in the real-world markets do not arrive in neat price-ordered cycles like those in the cyclical markets, the results from cyclical markets cannot be used to explain what happened in the real-world financial markets. The authors used these two types of markets to demonstrate that, if we want to understand complexity in the real-world financial markets, we should move away from the simple experimental economic models first introduced in the 1960s.

In the chapter, entitled "Does High-Frequency Trading Matter?", Chia-Hsuan Yeh and Chun-Yi Yang also investigated the impact of HFT on market stability, price discovery, trading volume, and market efficiency. However, instead of conducting real-time experiments using humans and robots, they developed an agent-based artificial stock market to simulate the interaction between HFT and non-HFT agents. In addition, unlike the robots in the previous chapter that used pre-generated permits to submit buy and sell orders for price matching, the agents in this study are more sophisticated in terms of using heuristics to make trading decisions. Moreover, the agents have learning ability to improve their trading strategies through experiences.

In their agent-based model, the trading speed is implemented as the agents' capability to process market information for decision-making. Although instant market information, such as the best bid and ask, is observable for all traders, only HFT agents have the capability to quickly process all available information and to calculate expected returns for trading decisions. Non-HFT agents, however, only have the capability to process the most recent k periods' information. The smaller that k is, the greater the advantage that the HFT agents have over non-HFT agents.

The institutional-level parameters that they investigated include:

- The number of HFT agents in the market (5, 15, 20);
- The activation frequency of HFT agents, which is specified by the number of non-HFT agents ($m = 40, 20, 10$) that have posted their quotes before an HFT agent can participate in the market. The smaller that m is, the more active the HFT agents are in participating in the trading.

Their simulation results indicated that market volatilities are greater when there are more HFT agents in the market. Moreover, a higher activation frequency of the HFT agents results in greater volatility. In addition, HFT hinders the price discovery process as long as the market is dominated by HFT activities. Finally, the market efficiency is reduced when the number of HFT agents exceeds a threshold, which is similar to that reported in the previous chapter.

1.2 Market Processes

The agriculture market in Luxembourg is thin, in terms of volume turnover, and the number of trades in all commodities is small. While the information on market products can be obtained through an annual survey of the farmers, the market products trading price information is not accessible to the public. In the chapter, entitled "Modelling Price Discovery in an Agent Based Model for Agriculture in Luxembourg," Sameer Rege, Tomás Navarrete Gutiérrez, Antonino Marvuglia, Enrico Benetto, and Didier Stilmant have proposed an agent-based model to simulate the endogenous price discovery process under buyers and sellers who are patient or impatient in submitting their bid/ask quotes.

In this model, agents are farmers whose properties (area, type, crops, etc.) are calibrated using the available survey data. The model is then used to simulate a market that contains 2242 farmers and ten buyers to trade 22 crops for four rounds. In each round, after all buyers and farmers have submitted the quantity and price for a commodity to buy or sell, the buyer who offers the highest price gets to purchase the desired quantity. If only partial quantity is satisfied under the offered price, the unmet quantity is carried over to the remaining rounds. Similarly, the sellers whose products do not get sold under the offered price are carried over to the remaining rounds. Based on the trading price in the initial round, buyers and sellers can adjust their bid/ask prices in the remaining rounds to achieve their trading goals.

Some buyers/sellers are impatient and want to complete the trading in the next round by increasing/decreasing the bid/ask prices to the extreme, while others are more patient and willing to gradually adjust the prices during each of the remaining three rounds. Based on their simulation, they found that the trading quantities and prices produced by patient and by impatient traders have very different distributions, indicating that traders' behaviors in submitting their bids/asks can impact the price discovery process in an economic market.

In the chapter, entitled "Heterogeneity, Price Discovery and Inequality in an Agent-Based Scarf Economy," Shu-Heng Chen, Bin-Tzong Chie, Ying-Fang Kao, Wolfgang Magerl, and Ragupathy Venkatachalam also used an agent-based model to investigate the price discovery process of an economic market. However, their agents are different from those in the previous chapter in that they apply individual and social learning to revise their subjective prices. The focus of this work is to understand how agents' learning behaviors impact the efficacy of price discovery and how prices are coordinated to reach the Walrasian equilibrium.

The model is a pure exchange economy with no market makers. Each agent has its own subjective prices for the commodities and agents are randomly matched for trading. The learning behavior of an agent is influenced by the intensity of choice λ, which specifies the bias toward the better-performing prices in the past. When λ is high, the agent trusts the prices that have done well (the prices can be from self and from other agents) and uses them to *adjust* its prices for the future trades. If λ is low, the agent is more willing to take risk incorporating prices that have not done well in the past for the future trades.

Their simulation results showed that agents with a low λ (0–3) have their subjective prices converging close to the Walrasian equilibrium. This means risk-taking agents are good at discovering prices toward the general equilibrium. Moreover, some agents with a large λ (>4) also have their market prices converging to the general equilibrium. The authors analyzed those high λ (>4) agents in more detail and found those agents to also be imitators who *copied* prices that have done well in the past to conduct most of their trades. This strategy enhanced their price coordination toward the general equilibrium.

In terms of accumulated payoffs, the agents with low λ (0–3) who also mixed innovation and imitation in adjusting their subjective prices have obtained medium or high payoffs. Meanwhile, the agents with high λ (>4) who are also imitators have received very high payoffs. Finally, the high λ (>4) agents who are also reluctant to imitate other agents' prices have received abysmal accumulated payoffs. Based on this emerging inequality of payoffs, the authors suggested that different learning behaviors among individuals may have contributed to the inequality of wealth in an economy.

In the chapter, entitled "Rational Versus Adaptive Expectations in an Agent-Based Model of a Barter Economy," Shyam Gouri Suresh also investigated market dynamics under agents with learning ability in a *pure exchange* or *barter economy*. In this direct exchange market, an agent can apply individual or social learning to predict the productivity level of his next exchange partner. Based on the prediction, the agent then decides his own productivity level. Under the individual learning mode, the prediction is based on the productivity level of the agent's current exchange partner while in the social learning mode, the prediction is based on the productivity level of the entire population.

In this model, the productivity level of an agent can be either high or low and there is a transition table that all agents use to decide their current productivity level according to their previous productivity. Additionally, an agent can incorporate his prediction about the productivity level of his next exchange partner to decide his current productivity level. This prediction can be carried out through either individual or social learning. Finally, to maximize his utility, an agent only adopts high productivity when his transition table indicates high productivity and his next exchange partner is also predicted to have high productivity.

The simulation results showed that the market *per capita outputs* or *average outputs* converged to low productivity under individual learning. This is because each time when an agent trades with another agent with low productivity, the agent will decide to produce low outputs in the next period regardless of the productivity specified by the transition table. This action in turn causes the agent he interacts with in the next period to produce low outputs in the period subsequent to the next. When an agent encounters another agent who has produced a high level of outputs, the agent will only adopt high productivity in the next period if the transition table also specifies high productivity. As a result, the market average outputs converge to low productivity.

By contrast, the market average outputs converge to high productivity under social learning, when the population size is large (100 in their case). This is because, in a large population, the likelihood of the population-wide distribution of productivity level being extreme enough to cause it to fall below the high-productivity threshold is low. Consequently, as all agents started with high productivity, the market average outputs remained high throughout the simulation runs.

In addition to the price discovery process and productivity level prediction, traders' learning behaviors might have impacted the forward premium in the foreign exchange market. In the chapter, entitled "Does Persistent Learning or Limited Information Matter in the Forward Premium Puzzle?, Ya-Chi Lin investigated whether the interactions between adaptive learning and limited market information flows can be used to explain the forward premium puzzle.

The forward premium puzzle in the foreign exchange market refers to the well-documented empirical finding that the domestic currency is expected to appreciate when domestic nominal interest rates exceed foreign interest rates [4, 10, 14]. This is puzzling because economic theory suggests that if all international currencies are equally risky, investors would demand higher interest rates on currencies expected to fall, and not to increase in value. To examine if investors' learning behaviors and their limited accessibility to market information may explain this puzzle, Lin designed a model where each agent can learn to predict the expected exchange rates using either full information (day t and prior) or limited information in the past (day $t-1$ and prior).

In this model, the proportion of agents that have access to full information, n, is an exogenous parameter. In addition, an agent has a learning gain parameter γ that reflects the learning strength. They simulated the model under different values of n, from 0.1 to 1, and γ, from 0.02 to 0.1, and found that the forward premium puzzle exists under small n for all values of γ. Moreover, when agents were allowed to choose between using limited or full information for forecasting, all agents switched to using full information (i.e., $n = 1$) and the puzzle disappeared for all values of γ. This suggests that limited information might play a more important role than learning in explaining the forward premium puzzle. However, regardless of the values of n and γ, the puzzle disappeared when tested in the multi-period mode. This indicates that limited information alone is not sufficient to explain the puzzle. There are other factors involved that will cause the puzzle to occur.

Herding is a well-documented phenomenon in financial markets. For example, using trading data from US brokerages, Barber et al. [3] and Kumar and Lee [13] showed that the trading of individual investors is strongly correlated. Furthermore, based on trading data from an Australian brokerage, Jackson [12] reported that individual investors moved their money in and out of equity markets in a systematic manner. To macroscopically study the effects of herding behavior on the stock return rates and on the price volatility under investors with different interaction patterns, in the chapter, entitled "Price Volatility on the Investor's Social Network," Yangrui Zhang and Honggang Li developed an agent-based artificial stock market model with different network structures.

In their interaction-based herding model, the trading decision of an agent is influenced by three factors: (1) personal belief; (2) public information, and (3) neighbors' opinions. Their work investigated the following institutional-level parameters:

- Agents' interaction structures: regular, small-world, scale-free, and random networks;
- Agents' trust in their neighbors' opinions (1–3);

Their simulation results showed that the market volatility is the lowest when the agents are connected in a regular network structure. The volatility increases when agents are connected under small-world or scale-free structures. The market volatility is the highest when agents are connected under a random network structure. This makes sense as the more irregular the agents' interaction pattern is, the higher the price fluctuations and market volatility. In addition, they found that the more an agent trusts in his neighbors' opinions, the greater the volatility of the stock price. This is also expected, as the more weight an agent attaches to his neighbors' opinions, the more diverse the trading decisions can be, and hence the higher that the price volatility becomes.

In the chapter, entitled "The Transition from Brownian Motion to Boom-and-Bust Dynamics in Financial and Economic Systems," Harbir Lamba also investigated herding behaviors in financial markets. However, instead of using a network model, he proposed a stochastic particle system where each particle is an agent and agents do not interact with each other. Agents' herding behavior is controlled by a herding parameter C, which drives the agents' states toward the market sentiment. Using this system, Lamba demonstrated that even a very low level of herding pressure can cause a financial market to transition to a multi-year boom-and-bust.

At time t, each agent i in the system can be in one of two possible states, owning the asset (+1) or not owning the asset (-1), according to its pricing strategy $[L_i(t), U_i(t)]$. When the asset market price r_t falls outside the interval of $L_i(t)$ and $U_i(t)$, agent i switches its state to the opposite state. In addition, when an agent's state is different from the state of the majority agents, its pricing strategy is updated at a rate of $C|\sigma|$, where σ is the market sentiment, defined as the average state of all agents. Hence, agents have a tendency to evolve toward the state of the majority agents. Finally, the market price r_t is the result of exogenous information and endogenous agent states generated by the agents' evolving pricing strategies.

Using 10,000 agents to simulate the market for 40 years, their results showed that even with a low herding parameter value $C = 20$, which is much lower than the estimated real market herding pressure of $C = 100$, the deviations of market prices away from the equilibrium resemble the characteristics of "boom-and-bust": a multi-year period of low-level endogenous activities that convince equilibrium-believers the system is in an equilibrium state with slowly varying parameters. There then comes a sudden and large reversal involving cascades of agents switching states, triggered by the change in market price.

1.3 Macroeconomy

Product innovation has been shown to play an important role in a firm's performance, growth, and survival in the modern economy. To understand how product innovation drives the growth of the entire economy, causing business cycle fluctuations, in the chapter, entitled "Product Innovation and Macroeconomic Dynamics," Christophre Georges has developed an agent-based macroeconomic model. In this model, a hedonic approach is used, where product characteristics are specified and evaluated against consumer preferences.

The macroeconomic environment consists of a single representative consumer and m firms whose products are described by characteristics that the consumer cares about. To satisfy the consumer's utility function, firms improve their product characteristic values through R&D investment. If the R&D indeed leads to product innovation that also recovers the cost, the firm grows. Otherwise, the firm becomes insolvent and is replaced by a new firm.
A firm can choose to invest or not to invest in R&D activities. The decision is based on the recent profits of other firms engaging in R&D and then tuned by the firm's own intensity parameter γ. When a firm decides to engage in R&D, the probability that the firm will experience successful product innovation increases.

Using 1000 firms and 50 product characteristics to run simulations, the results showed that the evolution of the economy's output (GDP) closely follows the evolution of the R&D investment spending. Meanwhile, the customer's utility grows over time, due to a long-term net improvement in product quality. Moreover, when the R&D intensity parameter γ is increased, the increased R&D spending drives up consumption, output, and utility. Finally, ongoing endogenous product innovation leads to ongoing changes in the relative qualities of the goods and the distribution of product shares. The distribution tends to become skewed, with the degree of skewness depending on the opportunities for niching in the product characteristics space. As the number of firms grows large, the economy's business cycle dynamics tends to become dominated by the product innovation cycle of R&D investment.

2 New Methodologies and Technologies for Complex Economic Dynamics

In addition to the previous ten chapters, this book also includes three chapters, which may not be directly related to agent-based modeling that may provide some useful ideas or tools that can help the modeling, simulation, and analysis of agent-based modeling. We shall also briefly highlight each of them here.

This book is mainly focused on financial markets and market processes. One issue naturally arising is related to how different markets are coupled or connected, and to what degree. In the chapter, entitled "Measuring Market Integration: U.S. Stock and REIT Markets," Douglas Blackburn and N.K. Chidambaran take up the issue of identifying the existence and extent of financial integration. This is an important methodological issue that empirical studies often encounter, given the complex relationships and heterogeneity that underpins financial markets. The authors identify a potential joint hypothesis problem that past studies testing for financial integration may have suffered from. This problem arises when testing for the equality of risk premia across markets for a common (assumed) set of risk factors; nonetheless, there is a possibility that a conclusion claiming a rejection of integration may actually stem from the markets not sharing a common factor.

Overcoming the joint hypothesis problem means disentangling the two issues and examining them separately. They present an approach based on factor analysis and canonical correlation analysis. This approach can be summarized in two steps. First, one should determine the correct factor model in each market and determine whether the markets share a common factor. Second, one should develop economic proxies for the shared common factor and test for the equality of risk premia conditional on a common factor being present. The equality of risk premia is tested *only if* common factors exist. The authors argue that this procedure in fact gives more power to the tests. They test their method on US REIT and stock markets for 1985–2013.

When one attempts to understand social systems as complex systems, for instance, through agent-based models, computers and simulations play a very important role. As the scale and scope of these studies increase, simulations can be highly demanding in terms of data-storage and performance. This is likely to motivate more and more researchers to use highly powerful, supercomputers for their studies as the field matures. In the chapter, entitled “Supercomputer Technologies in Social Sciences: Existing Experience and Future Perspectives,” Valery Makarov and Albert Bakhtizin document several forays into supercomputing in the social science literature.

The authors introduce some open-source platforms that already exist in the scientific community to perform large-scale, parallel computations. They discuss their hands-on experience in transforming a pre-existing agent-based model into a structure that can be executed on supercomputers. They also present their own valuable experiences and lessons in applying their models to supercomputers. From their experiences, C++ appears to be more efficient than Java for developing softwares running on supercomputers. The processes and issues related to translating a Java-based system into a C++ based system are also explained in the chapter.

Social sciences are distinct from natural sciences in terms of the potential of their theories to have an impact, for better or worse, on the actual lives of people. The great financial crisis of 2008, as some have argued, is a result of over reliance on unrealistic models with a narrow world-view, ignoring the complexities of the financial markets. Should more complex, sophisticated mathematical models be the solution? In the chapter, entitled “Is Risk Quantifiable?”, Sami Al-Suwailem, Francisco Doria, and Mahmoud Kamel take up this issue and examine the methodological issues related to the use of or over-reliance on “formal” models in the social sciences, in particular in economics and finance.

The authors question whether the indeterminacy associated with future economic losses or failures can be accurately modeled and systematically quantified using *formal* mathematical systems. Using insights from metamathematics—in particular, Kurt Gödel's famous theorems on incompleteness from the 1930s—they point to the inherent epistemological limits that exist while using formal models. Consequently, they argue that a systematic evaluation or quantification of risk using formal models may remain an unachievable dream. They draw several examples and applications from real-world financial markets to strengthen their argument and the chapter serves as a cautionary message.

3 Conclusion and Outlook

Computational economics is a growing field [6]. With the advancement of technologies, modern economies exhibit complex dynamics that demand sophisticated methods to understand. As manifested in this book, agent-based modeling has been used to investigate contemporary financial institutions of dark pools and high-frequency trading (chapters "Dark Pool Usage and Equity Market Volatility", "Modelling Complex Financial Markets Using Real-Time Human-Agent Trading Experiments", and "Does High-Frequency Trading Matter?"). Meanwhile, agent-based modeling is also used to shed light on the market processes or the price discovery processes by examining the roles of traders' characteristics (chapter "Modelling Price Discovery in an Agent Based Model for Agriculture in Luxembourg"), learning schemes (chapters "Heterogeneity, Price Discovery and Inequality in an Agent-Based Scarf Economy" and "Rational Versus Adaptive Expectations in an Agent-Based Model of a Barter Economy"), information exposure (chapter "Does Persistent Learning or Limited Information Matter in Forward Premium Puzzle?"), social networks (chapter "Price Volatility on Investor's Social Network"), and herding pressure (chapter "The Transition from Brownian Motion to Boom-and-Bust Dynamics in Financial and Economic Systems"). Each of these efforts made is a contribution to enhancing our understanding and awareness of market complexity. Given this extent of complexity, markets may not perform well for many reasons, not just economic ones, but also psychological, behavioral, sociological, cultural, and even humanistic ones. Indeed, market phenomena have constituted an interdisciplinary subject for decades [11, 15, 17–19]. What agent-based modeling can offer is a framework that can integrate these interdisciplinary elements into a coherent body of knowledge.

Furthermore, agent-based modeling can also help modern economies that have been greatly influenced by the big data phenomenon [7]. By applying computational methods to big data, economists have addressed microeconomic issues in the internet marketplaces, such as pricing and product design. For example, Michael Dinerstein and his co-authors [8] ranked products in response to a consumer's search to decide which sellers get more business as well as the extent of price competition. Susan Athey and Denis Nekipelov [2] modeled advertiser behavior and looked at the impact of algorithm changes on welfare. To work with big data, Google chief economist Hal Varian proposed machine learning tools as new computational methods for econometrics [20]. What will the impact of machine learning be on economics? "Enormous" answered Susan Athey, Economics of Technology Professor at Stanford Graduate School of Business. "Econometricians will modify the methods and tailor them so that they meet the needs of social scientists primarily interested in conducting inference about causal effects and estimating the impact of counterfactual policies," explained Athey [21]. We also expect the collaborations between computer scientists and econometricians to be productive in the future.

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References

1. Arthur, W. B., Holland, J., LeBaron, B., Palmer, R., & Tayler, P. (1997). Asset pricing under endogenous expectations in an artificial stock market. In W. B. Arthur, S. Durlauf, & D. Lane (Eds.), *The economy as an evolving complex system II* (pp. 15–44). Reading, MA: Addison-Wesley.
2. Athey, S., & Nekipelov, D. (2010). *A Structural Model of Sponsored Search Advertising Auctions*. Sixth ad auctions workshop (Vol. 15).
3. Barber, B. M., Odean, T., & Zhu, N. (2009). Systematic noise. *Journal of Financial Markets, 12*(4), 547–569. Amsterdam: Elsevier.
4. Bilson, J. F. O. (1981), The 'speculative efficiency' hypothesis. *Journal of Business, 54*(3), 435–451.
5. Chen, S. H. (2017). Agent-based computational economics: How the idea originated and where it is going. Routledge.
6. Chen, S. H., Kaboudan, M., & Du, Y. R. (Eds.), (2018). *The Oxford handbook of computational economics and finance*. Oxford: Oxford University Press.
7. Chen, S. H., & Venkatachalam, R. (2017). Agent-based modelling as a foundation for big data. *Journal of Economic Methodology, 24*(4), 362–383.
8. Dinerstein, M., Einav, L., Levin, J., & Sundaresan, N. (2018), Consumer price search and platform design in internet commerce. *American Economic Review, 108*(7), 1820–59.
9. Estola, M. (2017). Newtonian microeconomics: A dynamic extension to neoclassical micro theory. Berlin: Springer.
10. Fama, E. (1984). Forward and spot exchange rates. *Journal of Monetary Economics, 14*(3), 319–338.
11. Halteman, J., & Noell, E. S. (2012). *Reckoning with markets: The role of moral reflection in economics*. Oxford: Oxford University Press.
12. Jackson, A. (2004). The aggregate behaviour of individual investors, working paper. http://ssrn.com/abstract=536942
13. Kumar, A., & Lee, C. M. C. (2006). Retail investor sentiment and return comovements. *Journal of Finance, LXI*(5). https://doi.org/10.1111/j.1540-6261.2006.01063.x
14. Longworth, D. (1981). Testing the efficiency of the Canadian-U.S. exchange market under the assumption of no risk premium. *The Journal of Finance, 36*(1), 43–49.
15. Lonkila, M. (2011). *Networks in the Russian market economy*. Basingstoke: Palgrave Macmillan.
16. Petrescu, M., Wedow, M., & Lari, N. (2017). Do dark pools amplify volatility in times of stress? *Applied Economics Letters, 24*(1), 25–29.
17. Rauch, J. E., & Casella, A. (Eds.), (2001). *Networks and markets*. New York: Russell Sage Foundation.

18. Staddon, J. (2012). *The malign hand of the markets: The insidious forces on wall street that are destroying financial markets—and what we can do about it*. New York: McGraw Hill Professional.
19. Tuckett, D. (2011). *Minding the markets: An emotional finance view of financial instability*. Berlin: Springer.
20. Varian, H. R. (2014, Spring). Big data: New tricks for econometrics. *Journal of Economic Perspectives, 28*(2), 3–28.
21. What Will The Impact Of Machine Learning Be On Economics? https://www.forbes.com/.../what-will-the-impact-of-machine-learning-be-on-economics/), Forbes, Jan 27, 2016.
22. Wolfram, S. (2002). *A new kind of science* (Vol. 5). Champaign: Wolfram Media.