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Understanding the complex dynamics of financial markets through microsimulation

Qiu, G.

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Chapter 7

Conclusions and Future Prospects

7.1 Concluding discussion

In this work, we apply microsimulation to study the complex dynamics of financial markets. We focus on those aspects of market dynamics that are characterized by some persistent patterns empirically observed in financial time series of which the root cause can hardly be explained by the traditional economic theories, as discussed extensively in Chapters 2 and 3. This chapter summarizes the research that has been presented in this thesis and provides some ideas for future work.

7.1.1 Answers to the research questions

As stated in Chapter 1, this research focuses on two most active types of market, i.e., stock markets and options markets, to address two research questions. These questions and the corresponding findings that have been obtained from this research can be summarized as follows:

- a. What are the principal mechanisms underlying stylized facts observed in stock markets? Are these mechanisms common across explanations provided by the well-established microsimulation models proposed in the literature?

We have developed a cellular automaton (CA) model and have performed a detailed investigation regarding the mechanism underlying the dynamics of stock markets (see Chapter 4). The model can reproduce, in a simple and robust manner, the main characteristics observed in empirical financial time series. Our simulations and analysis suggest that long-range agent interactions, which are responsible for large price variations, can form from local interactions. Volatility clustering is associated with the variation in agents' trading activity, a slow process in comparison to the variation in the influence of news. Heavy-tailed distributions of return are related to both large price variations and volatility clustering. Finally, these non-Gaussian distributions are produced by agents' behavior in response to the arrival of news, even though the influence of news is assumed to follow a Gaussian random process. In a general sense, these causes of heavy tails and volatility clustering appear to be common among some well-established microsimulation models that have confirmed the main characteristics of financial markets.

- b. What is the origin of the poorly understood volatility smile phenomenon observed in option markets and what are the driving factors determining the shape and the dynamic properties of the smile?

We have developed a microsimulation model to investigate the market mechanism governing the volatility smile (see Chapters 5 and 6). In our model, the typical behavior of the most active options traders, i.e., speculators and arbitrageurs, is adopted and the prices of the options are determined by demand and supply. Our results agree with empirical studies in respect to the shape and dynamic properties of the smile. The detailed analysis shows that, although traders have distinct trading interests, their behavior leads to contests regarding the option prices and eventually the shape of the smile. In addition, the level of the smile is positively related to the variance of speculators' expected prices. Moreover, the deviation of the mean of speculators' expected prices from the current price of the underlying is crucial to the shape of the smile. The cases that the former is smaller than, equal to, and larger than the latter, will give rise to respectively a downward

sloping, a symmetric, and a upward sloping curve. In Chapters 5 and 6, we demonstrate rigorously that these findings are robust with respect to the types of trading behavior included in the microsimulations and the actual values employed for the different model parameters. These results strongly suggest that the volatility smile is a natural consequence of traders' heterogeneous behavior and expectations about the future and confirm that individual trading preferences indeed play a critical role in the dynamics of the implied volatility curve.

While the above discussion briefly summarizes the main findings of the research, in the following sections we discuss some general insights obtained from this research and our extensive literature study. We will focus on aspects related to the characteristics of complex system dynamics and the methodology employed in this work.

7.1.2 Complex dynamics can emerge from simple behavior

Many phenomena which are difficult to explain with the traditional economic framework and considered irregular can be conveniently reproduced in microsimulations. In contrast to the standard models, which view the stylized facts of financial markets as the result of exogenous factors, the microsimulation approach considers these features as emergent properties resulting from the internal dynamics, i.e., traders' behavior and their interactions. Importantly, as shown by our models and many other microsimulation models, the behavior does not need to be complicated, i.e., complex market dynamics can emerge from *simple* and ordinary trading behavior.

Specifically, interaction is a key factor in generating the complex dynamics. Interactions in financial markets can be categorized into two broad types: Those among traders and those between prices and traders. Imitators' behavior is of the first type, while speculators' behavior is of the second one.

Imitation is commonly exhibited in financial markets. Although imitative behavior is associated with diverse activities in financial markets and researchers have focused on different kinds of imitation, all types of imitation described in

the various agent-based models share a single feature: The imitators mimic the transactions that have been performed by other traders. From this perspective, we adopt a very simple but representative form of imitation in our cellular automaton model of stock markets: The imitators take the average transaction quantities of their local neighbors at the previous time step as their current quantities. Interestingly, such a simple framework can reproduce the large price jumps observed in real markets.

Speculators typically rely on their expectations about the price in the future. In options markets, this is particularly true because options are contingent claims by nature: The payoffs of options are eventually determined by the future prices of the underlying assets. Speculators trade according to their expectations about the price and their trading will in turn change the price. These micro-macro interactions are typical of financial markets. In our options market model, the speculators' expected prices play a crucial role. They determine the traders' expected profits and ultimately their actions. Surprisingly, by examining the effects of the changes in only the mean and variance of the expected prices, all the main stylized facts related to the volatility smile can be convincingly explained.

7.1.3 Microsimulation: Necessity and difficulty

7.1.3.1 Microscopic modeling is necessary for understanding market dynamics

Financial markets consist of a large number of heterogeneous agents trading in diverse financial instruments. Traders' behavior and interactions give rise to the macroscopic price dynamics, which in turn influences the microscopic behavior and interactions. This process is highly nonlinear and difficult to describe analytically. Traditional approaches in finance and economics to study aggregative phenomena either are purely macroscopic, or rely on top-down construction based on a number of unrealistic assumptions mainly for the sake of analytical tractability. Heterogeneity is neglected and interactions between traders play no role in the explanation of the phenomena. This may account for the inability of the mainstream economic theories to explain the complex market dynamics characterized by the stylized facts.

On the other hand, many studies of financial market dynamics are difficult to carry out experimentally. An obvious reason is that experiments with regard to large scale markets using real people are usually too expensive to conduct. Moreover, in experiments the subjects no longer behave naturally, so that the resulting conclusions might not be convincing.

Microsimulation enables us to explore complex economic dynamics from the bottom up. With microsimulations, we study a complex system by directly modeling its individual elements and their interactions. The macroscopic behavior of the system will eventually emerge from the microdynamics. Microsimulation has shown great potential for more realistically modeling complex dynamical systems in economics and finance (Levy et al. (2000)). In addition, it facilitates the testing of existing economic or financial models and theories, and the development of new theories and models (Tsfatsion (2002)). Moreover, microsimulations are much more cost feasible for investigating phenomena observed in large scale financial markets. In brief, microsimulation is an indispensable method for deeply studying market dynamics.

7.1.3.2 Difficulty in implementing microsimulations

Although the necessity of microsimulation is being recognized, the implementation of this method is by no means easy. Here we list a few difficult points identified from our own experience and literature study.

A difficult point lies in the identification of the types of trader and trading behavior relevant to the phenomenon under investigation. Financial markets are comprised of a large number of heterogeneous traders with distinct interests and strategies, apart from different amounts of capital, channels of information, restrictions, etc. However, only some specific types of trader and trading behavior are directly related to certain stylized facts and usually the main difficulty lies in accurately identifying them. A obvious reason for this difficulty stems from the fact that we can hardly carry out large scale experiments with real traders to study the complicated cause-effect relations among different objects in real markets. (In fact, this is the very reason for our employment of microsimulation.) Therefore, to explain the same phenomenon, microsimulation modelers might select different

types of trader and/or trading behavior and develop different models. Certainly, models are different in explanatory power. In our opinion, apart from other criteria, a microsimulation model is considered good if it can qualitatively and quantitatively explain most relevant stylized facts.

Another difficult point is encountered in the simplification of the selected traders. In microsimulations, we face the dilemma of modeling traders as realistically as possible or exhibiting the causal relations of the market dynamics as clearly as we can. Unrealistic modeling is unacceptable, whereas models with a host of details can conceal the mechanisms of interest and will be of no use. A model is just a representation of a system for addressing a certain problem. It should be built by including just the essential features necessary for addressing a certain problem under study and excluding aspects that are considered secondary. However, it is difficult to determine the boundary that separates the the most relevant elements from secondary details. In overcoming this difficulty, we only adopt the most typical heterogeneous trading behavior in real markets which is complex enough to cover traders' main characteristics, in the meantime simple enough for revealing the underlying market mechanisms.

Yet another difficult point arises in the adoption of parameter values. Because microsimulation models are just concise representations of real markets, parameters are unavoidable. However, since microsimulation is fairly new in economics and finance, no empirical or experimental studies related to many parameters in MS models have been carried out. Consequently, we lack empirical estimates that can be used to calibrate the model parameters. In the absence of relevant empirical observations for some parameters, we have performed qualitative and quantitative analyzes to ensure that the findings obtained from our models are robust.

7.2 Future work

The main insight we have obtained is that the complex market dynamics is generated by heterogeneous traders' behavior and interactions. Based on and guided by this understanding, we suggest two directions for future work: Studying the

multiscale nature of the complex dynamics of financial markets and exploring the applications of our research results to financial practice.

7.2.1 Multiscale modeling of financial markets

We have developed microsimulation models for understanding the dynamics of stock markets and that of option markets separately. In these models, the market participants only trade either stocks or options. However, in reality, many traders deal with portfolios, which are collections of different financial instruments and typically contain derivatives and their corresponding underlying securities. They may adjust their positions in some instruments based on the prices of some other instruments. This will generate links among different markets and further increase the complexity of financial economy.

For example, delta hedging is a strategy widely used by derivative dealers to reduce or eliminate the risk of their portfolios associated with price movements in the underlying assets. (For a detailed description of this strategy, see Hull (2003).) Importantly, because the price of the underlying asset changes over time, the dealers' positions remain delta neutral only for a short period of time and the hedges have to be adjusted periodically. Delta hedging is therefore a dynamic hedging scheme and it connect the demand and supply of the underlying asset to the prices of the options, and eventually the demand and supply of the options. In this manner, the price dynamics of the underlying asset is explicitly linked to that of the corresponding derivatives, although the degree of correlation is certainly dependent on the relative trading volumes. What can be expected if the trading volume of dynamic hedging is comparable to those of other traditional trading strategies? Considering the fact that in reality traders use advanced hedging strategies which connect markets of different types of underlying or derivative security, this is an important issue to address.

7.2.2 Applications to practice

Financial practitioners should benefit from the better understanding of the complex dynamics of financial markets achieved through microsimulations. However, there is still a large gap between the understanding of the underlying mechanisms

and its implementation in day-to-day practice. Future research should endeavor to cover this gap. Our microsimulation models illustrate the importance of heterogeneous traders' beliefs and behavior for the market dynamics. In developing new approaches to risk management or other financial practices, collective human behavior should somehow be incorporated. Surely, this is one of the greatest challenges of this field which in our opinion can only be addressed by combining insights and principles from mathematical finance, agent-based simulations and behavioral finance.