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Comparison of a Fuzzy-Logic Based Bidding Strategy with Other Strategies in Dynamic Double Auctions

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Abstract

Double auctions are commonly used market mechanisms on the world. Double auctions constitute one of the most complex market mechanisms by allowing both buyers and sellers to make price offers. Complexity theory is an emerging scientific paradigm which deals with complex systems and sometimes called a scientific revolution. One of the main analysis tools in complexity paradigm is agent based simulations. With agent based simulations agent behaviors can be modeled and collective outputs of agent interactions can be obtained from the simulations. Double auctions are complex systems in which buyers and sellers interact with each other. Although double auctions are widely used on the world theoretical works on double auctions are few. Main reason of this is the complexity of double auctions. Complexity theory and agent based simulations promises new opportunities for modeling and understanding double auctions. In this work, we investigated a kind of double auction which is called dynamic double auction by using agent based simulations. In our simulations we modeled trader (agent) behaviors with bidding strategies. We utilized seven bidding strategies. Two of them are based on fuzzy logic (FFL and SFL) and four of them are based on price targeting. We also used zero intelligence strategy for comparison purposes. In our simulations we compared second fuzzy logic (SFL) strategy with other strategies and demonstrated that SFL strategy has always higher profit than other strategies.

Keywords: Double Auction, Bidding Strategies, Fuzzy Logic, Agent-based Simulation.

1. Introduction

Complexity theory brought new views to the science (Bar-Yam, 1997; Miller and Page, 2009; Waldrop, 1993; Boccara, 2010; Newman, 2011). Complexity theory originated from cybernetics (Ashby, 1961; Wiener, 1961), chaos (Lorenz and Haman, 1996;

Alligood et al., 1996) and system theories (Von Bertalanffy, 1968) and constitutes a scientific revolution as described by Khun (1970).

The history of scientific studies on complexity and complex systems not go too far back. Until recently the analytical method was the primary and dominant method in science. However analytical method's limitations for explaining complex systems are discovered recently. But the advent of computer technology presents new opportunities for modeling and understanding of complex systems. Thus studies on complex systems gained momentum recently (Bar-Yam, 2018; Fieguth, 2017; Morales et al., 2018; Sánchez and Newman, 2018).

Economies and markets are complex systems which includes many individuals and interactions between these individuals (Anderson et al., 2018; Arthur, 2018; Markose, 2005). Despite the apparent complexity of economies and markets neoclassical economists established simple models including equations and ideas based on equilibrium. Developments in complexity theory made modeling of complex economic systems with computer possible (Boero et al., 2015; Cristelli, 2014; Pyka and Foster, 2015). Thus complexity paradigm in economics emerged as a new paradigm distinguished from neoclassical paradigm (Montgomery, 2000).

One reflection of complex systems paradigm to economics is Agent-based Computational Economics (ACE) (Tesfatsion and Judd, 2006; Gallegati et al., 2017). Under ACE paradigm researchers simulates economic systems by using autonomous interacting agents. In these simulations agent behaviors are modeled computationally. Standard theories are insufficient to illuminate working and results of financial markets (Arthur, 1999; Statman, 1995). In this context, complexity theory promises new opportunities for understanding of financial markets. Financial markets are complex systems, in which many heterogeneous agents (traders) interact with each other (Johnson, 2003; May, 2008). These markets are characterized with dispersed and local interactions, lack of a global controller, continuous adaptation and out of equilibrium dynamics. In every market there is a market institution which governs transactions between traders. Auctions are main market mechanisms used in financial markets (Mochon and Sáez, 2015; Hubbard and Paarsch, 2016; Klemperer, 2004). There are many types of auctions but these can be categorized as one sided auctions and double auctions. Theoretic and analytic studies on one sided auctions (Cox et al., 1982; Milgrom and Weber, 1982) gained more success than double auctions. Double auctions constitute a complex market mechanism by allowing both sellers and buyers to send price offers (Friedman, 2018). There are also many types of double auctions. The double auction mechanism used in this study is called dynamic double auction since the cost and redemption values can change in each period.

There are few theoretical and analytical studies on double auction which attempt to explain price formation in double auctions (Easley and Ledyard, 1993; Friedman, 1984, 1991; Wilson, 1987). But these studies assume enforcing and unrealistic assumptions. Double auctions are also investigated in the literature by using laboratory experiments with human subjects (Smith, 1962, 1992; Smith and Williams, 1992; Cason and Friedman, 1996). These experiments revealed that double auction is a very efficient market mechanism even with small number of traders. But these experiments have some limitations. Firstly, these experiments are costly so its size must be small. Secondly, human subjects' some qualifications are not controlled. On the other hand in computer simulations of double auctions, agents' qualifications can be controlled and their effects on results can be separated. Moreover computer simulations are cheap, easy and provide more data (Haijun et al., 2016; Gode and Sunder, 1993; Rust et al., 1992, 1994; Cliff, 1997; Chiarella and Iori, 2002; Preist and van Tol, 1998; Raberto and Cincotti, 2005). That's why in this work, we used simulation approach to study double auction.

2. Bidding strategies used in simulations

In this study, bidding strategies are simulated for dynamic double auction developed by Unal and Aladag (2018). These bidding strategies are named below.

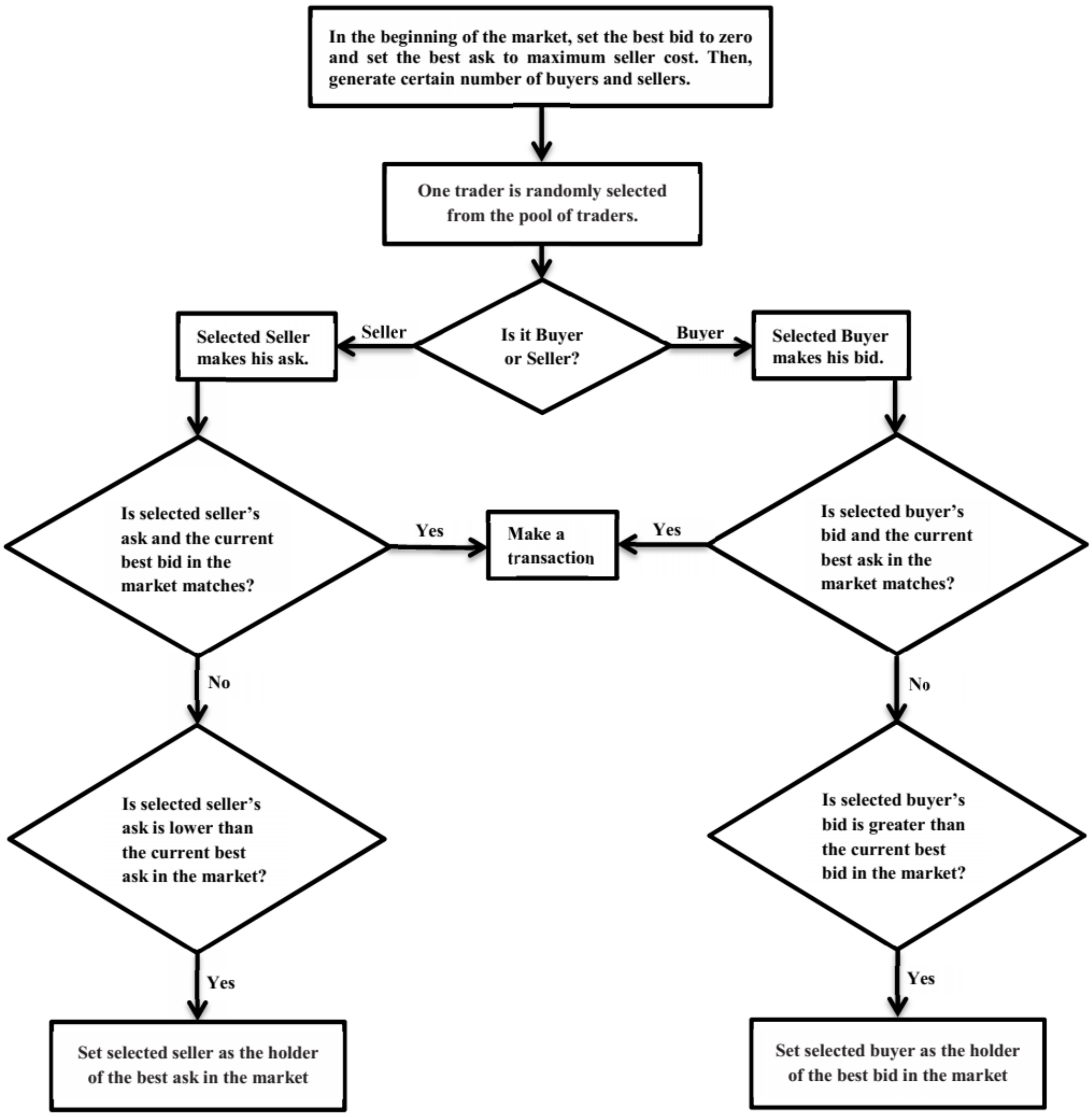

Figure 1. Flowchart of market mechanism

1. Zero intelligence strategy (ZI Strategy)
2. Last price targeting strategy (LPT Strategy)
3. Median price targeting strategy (MPT Strategy)
4. Best bid or ask targeting strategy (BBAT Strategy)
5. Cost or value targeting strategy (CVT Strategy)
6. First fuzzy logic-based bidding strategy. (FFL Strategy)
7. Second fuzzy logic-based bidding strategy. (SFL Strategy)

In the ZI Strategy (1), traders make their price offers randomly. In price targeting strategies (2-5) traders aim a target price (which differs in each strategy) and approach this target price with an amount of learning rate. Fuzzy logic-based strategies (6-7) utilize fuzzy logic inference systems when offering bid and ask prices. SFL strategy is more advanced strategy than FFL strategy in terms of number of fuzzy rules in rule bases and output membership functions resolution. Details of these strategies above can be found in Unal and Aladag (2018). The flowchart of our double auction market mechanism is given in Figure 1.

3. Results and discussions

Main motivation of Unal and Aladag (2018) is to compare these seven strategies with each other. In their study, buyers and sellers are the same types in market simulations. However, the main aim of this study is to compare SFL Strategy with other strategies. So in our simulations either buyers or sellers are SFL and corresponding sellers or buyers are one of the other strategies above. We compared SFL strategy with each of the other strategies by measuring mean total profits for sellers and buyers. In Table 1-6 comparison results of SFL buyers and other sellers are shown and in Table 7-12 comparison results of SFL sellers and other buyers are shown. As seen from these tables SFL traders have statistically significant (by using *t* tests) higher mean (obtained from 400 replications) total profits than other traders. We also investigate the mean total profit differences between SFL traders and other traders. For this purpose we computed total mean profit differences between SFL buyers and other sellers as well as SFL sellers and other buyers. Calculation results are shown in Table 13-14. As seen from these tables we can rank profit differences as: (SFL – BBAT) > (SFL – CVT) > (SFL – MPT) > (SFL – LPT) > (SFL – ZI) > (SFL – FFL). So in the market simulations with price targeting strategies profits are distributed more asymmetrically on the behalf of SFL traders.

Table 1. Comparison of ZI Sellers and SFL Buyers

		N	Mean	Std. Deviation	Std. Error Mean
Total Profit	ZI Sellers	400	638.6239	129.76996	6.48850
	SFL Buyers	400	1736.4228	262.08502	13.10425

Table 2. Comparison of LPT Sellers and SFL Buyers

		N	Mean	Std. Deviation	Std. Error Mean
Total Profit	LPT Sellers	400	322.6603	69.11444	3.45572

	SFL Buyers	400	1898.6910	318.64681	15.93234

Table 3. Comparison of MPT Sellers and SFL Buyers

		N	Mean	Std. Deviation	Std. Error Mean
Total Profit	MPT Sellers	400	279.5783	62.54045	3.12702
	SFL Buyers	400	1979.6452	323.79942	16.18997

Table 4. Comparison of BBAT Sellers and SFL Buyers

		N	Mean	Std. Deviation	Std. Error Mean
Total Profit	BBAT Sellers	400	128.2390	60.09111	3.00456
	SFL Buyers	400	2039.1222	291.68908	14.58445

Table 5. Comparison of CVT Sellers and SFL Buyers

		N	Mean	Std. Deviation	Std. Error Mean
Total Profit	CVT Sellers	400	132.5782	65.12919	3.25646
	SFL Buyers	400	2028.6047	315.82987	15.79149

Table 6. Comparison of FFL Sellers and SFL Buyers

		N	Mean	Std. Deviation	Std. Error Mean
Total Profit	FFL Sellers	400	890.4000	172.46941	8.62347
	SFL Buyers	400	1548.8299	230.83134	11.54157

Table 7. Comparison of SFL Sellers and ZI Buyers

		N	Mean	Std. Deviation	Std. Error Mean
Total Profit	SFL Sellers	400	1732.1707	283.84379	14.19219
	ZI Buyers	400	623.3153	127.90163	6.39508

Table 8. Comparison of SFL Sellers and LPT Buyers

		N	Mean	Std. Deviation	Std. Error Mean
Total Profit	SFL Sellers	400	1921.7960	304.23786	15.21189
	LPT Buyers	400	330.8002	76.65797	3.83290

Table 9. Comparison of SFL Sellers and MPT Buyers

		N	Mean	Std. Deviation	Std. Error Mean
Total Profit	SFL Sellers	400	1956.1213	297.91671	14.89584
	MPT Buyers	400	279.6921	62.82023	3.14101

Table 10. Comparison of SFL Sellers and BBAT Buyers

		N	Mean	Std. Deviation	Std. Error Mean
Total Profit	SFL Sellers	400	2037.9169	311.57508	15.57875
	BBAT Buyers	400	134.3522	66.00628	3.30031

Table 11. Comparison of SFL Sellers and CVT Buyers

		N	Mean	Std. Deviation	Std. Error Mean
Total Profit	SFL Sellers	400	2029.7146	313.76042	15.68802
	CVT Buyers	400	130.9019	59.10684	2.95534

Table 12. Comparison of SFL Sellers and FFL Buyers

		N	Mean	Std. Deviation	Std. Error Mean
Total Profit	SFL Sellers	400	1445.6225	206.61992	10.33100
	FFL Buyers	400	959.0972	181.36316	9.06816

Table 13. Mean total profit difference between SFL Buyers and Other Sellers

	Mean Total Profit Difference
(SFL Buyers) – (ZI Sellers)	1097.7989
(SFL Buyers) – (LPT Sellers)	1576.0307
(SFL Buyers) – (MPT Sellers)	1700.0669
(SFL Buyers) – (BBAT Sellers)	1910.8832
(SFL Buyers) – (CVT Sellers)	1896.0265
(SFL Buyers) – (FFL Sellers)	658.4299

Table 14. Mean total profit difference between SFL Sellers and Other Buyers

	Mean Total Profit Difference
(SFL Sellers) – (ZI Buyers)	1108.8554
(SFL Sellers) – (LPT Buyers)	1590.9958
(SFL Sellers) – (MPT Buyers)	1676.4292
(SFL Sellers) – (BBAT Buyers)	1903.5647

(SFL Sellers) – (CVT Buyers)	1898.8127
(SFL Sellers) – (FFL Buyers)	486.5253

4. Conclusions and future works

Although complexity theory is a new paradigm in science it achieved remarkable development in recent decades. This fast development is related with the advancement of computer technology. One of the main tools of complexity theory is agent based simulations. In this paper, we performed agent based simulations of dynamic double auction markets by using different bidding strategies. We compared SFL traders' profits with other traders' profits and demonstrated that SFL traders have the highest profits. Our results indicate that profit distribution between sellers and buyers are depends on the bidding strategies of traders. As a result of the simulation study, we revealed that profit distribution is very asymmetric for price targeting strategies. However, profit distribution is more symmetric in simulations contains FFL strategy. That is, price targeting strategies produce lower total profits than produced by FFL strategy. Results obtained in this study confirm the findings of the study by Unal and Aladag (2018). For future work, double auction market can be simulated with more heterogeneous traders who have more than two strategy types. Also, a switching mechanism can be imposed on traders in future studies.

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