Journal of Economic Dynamics & Control 61 (2015) 245–268

Contents lists available at ScienceDirect

Journal of Economic Dynamics & Control

journal homepage: www.elsevier.com/locate/jedc

Learning, information processing and order submission in limit order markets

Carl Chiarella [a], Xue-Zhong He [a], Lijian Wei [b,*]

[a] University of Technology Sydney, UTS Business School, PO Box 123, Broadway, NSW 2007, Australia
[b] Sun Yat-Sen University, Sun Yat-Sen Business School, No. 135, West Xingang Road, Guangzhou 510275, PR China

ARTICLE INFO

Article history:
Received 17 September 2014
Received in revised form
26 September 2015
Accepted 28 September 2015
Available online 9 October 2015

JEL classification:
G14
C63
D82

Keywords:
Limit order book
Order submission
Genetic algorithm learning
Asymmetric information
Probability of informed trading

ABSTRACT

By introducing a genetic algorithm learning with a classifier system into a limit order market, this paper provides a unified framework of microstructure and agent-based models of limit order markets that allows traders to determine their order submission endogenously according to market conditions. It examines how traders process and learn from market information and how the learning affects limit order markets. It is found that, measured by the average usage of different group of market information, trading rules under the learning become stationary in the long run. Also informed traders pay more attention to the last transaction sign while uninformed traders pay more attention to technical rules. Learning of uninformed traders improves market information efficiency, but not necessarily when informed traders learn. Opposite to the learning of informed traders, learning makes uninformed traders submit less aggressive limit orders and more market orders. Furthermore private values can have significant impact in the short run, but not in the long run. One implication is that the probability of informed trading (PIN) is positively related to the volatility and the bid-ask spread.

> "*It is the uninformed traders who provide the liquidity to the informed, and so understanding their behavior can provide substantial insight and intuition into the trading process…(an) open question is what traders can learn from other pieces of market data, such as prices.*" O'Hara (2001)

1. Introduction

Though raised by O'Hara for more than a decade ago, our understanding of uninformed traders' behavior and what traders can learn from market information is still very limited, in particular in limit order markets, which are the dominant financial markets. Because of information asymmetry and growing complexity in order flows and trading in limit order markets, the current literature mainly focuses on the behavior of informed traders and simplifies the behavior of uninformed traders by introducing private value (Goettler et al., 2009) or time preference (Rosu, 2015) to exogenously determine the order choice of uninformed traders.

In this paper, we focus on the behavior heterogeneity between informed and uninformed traders when they share the same learning algorithms. Different from informed traders, uninformed traders have delayed information about the

* Corresponding author.
E-mail addresses: Carl.Chiarella@uts.edu.au (C. Chiarella), Tony.He1@uts.edu.au (X.-Z. He), weilijian1981@163.com (L. Wei).

http://dx.doi.org/10.1016/j.jedc.2015.09.013
0165-1889/

fundamental value. To examine how traders process market information, we introduce a genetic algorithm (henceforth GA) learning with a classifier system[1] to classify market information into different groups according to market conditions. By combining information processing of market conditions and order choice (limit/market orders to buy/sell) into the *trading rule*,[2] the behavior heterogeneity of traders is endogenously emerged from their learning and trading. Put differently, we allow traders to co-evolve trading rules with gain information from short-term price movement and, most importantly, the state of the order book itself. We show that, measured by the average usage of different group of market information, the trading rules under the GA learning become stationary in the long run. This helps to understand the effect of learning on order profit, information efficiency, order submission and liquidity. We find that, with respect to information processing, market information is more useful for uninformed traders than informed traders, in particular informed traders pay more attention to the last transaction sign while uninformed trader pay more attention to some technical rules. With respect to the impact on the market, learning of uninformed traders improves market information efficiency, which is not necessarily the case when informed traders learn. With respect to order submission, learning makes uninformed traders submit less aggressive limit orders but more market orders and patient limit orders, while it makes informed traders submit less market orders and more aggressive limit orders. In general, both informed and uninformed traders provide liquidity to the market at approximately the same rate, which is different from that in market-maker markets. The results provide some insight into the information processing and order submission behavior of traders when they learn from market information in limit order markets. They also lead to an implication on the probability of informed trading (PIN).

This paper contributes to the literature of market microstructure in limit order markets and agent-based computational finance with adaptive learning by integrating them into a unified framework to address the open question from O'Hara. In the literature of market microstructure in limit order markets, the endogenous order choice based on the order book conditions is a core and challenging issue, as highlighted by Rosu (2012).[3] In particular, modeling a dynamic limit order book is very challenging. As pointed out by Goettler et al. (2009) (p. 68), "*a model that incorporates the relevant frictions of limit-order markets* (*such as discrete prices*, *staggered trader arrivals, and asymmetric information*) *does not readily admit a closed-form solution*." To overcome this challenge, we introduce a GA learning with classified rules into a limit order market. Within this framework, a trading rule contains two parts: market conditions and actions. The market conditions may include market information of bid, ask, mid-price (the bid-ask midpoint), historical prices, order book depth and the transaction sign of the last market order. Classified rules, such as "*the current ask is lower than the last ask*", are used for traders to process order book information. The actions may include buy/sell at market/limit orders. For example, one trading rule could be "*when the current ask is lower than the last ask and the current bid-ask spread is smaller than before*, *traders choose a market buy*". Trading rules are then evolved according to the GA based on their historical performance. When a trader enters the market, he/she chooses the best trading rule from the selected candidates that match the current market conditions. In this way, the GA allows traders to learn from their historical experience and endogenously make order choice according to the current market conditions.

We show that, measured by the average usage frequency of different groups of information, trading rules become stationary under the GA learning in the long run, demonstrating the effectiveness of the learning. We also show that, with the GA learning, the average usage of all groups of information is higher for uninformed traders than for informed traders. In general, the order profit/loss of traders is improved/reduced and the learning is more valuable for uninformed traders than for informed traders. Among all the market information, informed traders use more information of the last transaction sign, while uninformed traders use more information related to technical rules. Furthermore, traders submit more limit orders than market orders and the learning reduces the bid-ask spread; however, the learning makes informed traders submit less market orders and more aggressive limit orders while uninformed traders submit less aggressive limit orders but more market orders and limit orders at or away from the quotes. Moreover, by using the information of the last transaction sign, informed traders improve their order profit, submit more market orders and hence consume more liquidity but reduce the bid-ask spread. By using the technical rules, uninformed traders reduce their loss, market information efficiency is improved but the bid-ask spread becomes wider. In a robustness analysis, we find that private value for uninformed traders can affect trading rules and limit order market significantly in the short run, but not in the long run. This result is different from Goettler et al. (2009) who find that private values mainly determine the order submission of uninformed traders. The result of endogenous order choice provides insight into how traders process order book information and how the learning affects the market liquidity through traders' order submission.

This paper also contributes to the literature of agent-based computational finance with adaptive learning.[4] On one hand, two surveys of Chen et al. (2012) and Gould et al. (2013) have pointed out that after several prototypes have successfully replicated a number of financial stylized facts of the low frequency data, the next milestone is to see whether the agent-based model can also be used to replicate the features either in the high frequency domain or the features in market microstructure, which may be considered as the two missions of the second-generation agent-based financial models. While

[1] Both GA and classifier system are first introduced by Holland (1975), a typical application in financial markets is the SFI-ASM (see Arthur et al., 1997).

[2] Our trading rule is a condition/action rule which is a typical Holland classifier; similarly, Arthur et al. (1997) called their condition/forecast rule as "predictor".

[3] Rosu (2015) solves the stationary equilibrium by assuming that traders can continuously monitor the market and reenter the market to modify their limit orders freely at anytime.

[4] We thank anonymous referees for suggestions of highlighting this aspect and the following discussions.