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The effect of genetic algorithm learning with a classifier system in limit order markets

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ABSTRACT

By introducing a genetic algorithm with a classifier system as a learning mechanism for uninformed traders into a dynamic limit order market with asymmetric information, this paper examines the effect of the learning on traders' trading behavior, market liquidity and efficiency. We show that the learning is effective and valuable with respect to information acquisition, forecasting, buy–sell order choice accuracies, and profit opportunity for uninformed traders. It improves information dissemination efficiency and reduces the information advantage of informed traders and hence the value of the private information. In particular, the learning and information become more valuable with higher volatility, less informed traders, and longer information lag. Furthermore, the learning makes not only uninformed but also informed traders submit more limit orders and hence increases market liquidity supply.

1. Introduction

In financial markets with both informed and uninformed traders, it is well recognized that an effective learning of uninformed traders can improve market efficiency. Although the impact of various learning behaviors on market efficiency has been studied, such impact can differ across markets, in particular in limit order markets. Due to the popularity and complexity of limit order markets, it is important to understand how uninformed traders can learn and, more importantly, how learning can affect traders' trading behavior, market efficiency and liquidity. With rapid development of internet and information technology, private information becomes short-lived. When informed traders trade optimally and actively to take the advantage of their private information, they inevitably release part of their private information to the market. If uninformed traders can learn effectively, market is expected to becomes more efficient, hence improving the profit opportunity of uninformed traders while reducing the profit of informed traders. Therefore it becomes very important to understand how uninformed traders can learn effectively and how the learning can affect trading behavior, liquidity, and efficiency in limit order markets. In this paper, we introduce genetic algorithm with classifier system as a learning mechanism for uninformed traders into a dynamic limit order market model with asymmetric information and examine the value of the learning and its impact on traders' trading behavior, market liquidity, and efficiency.

The importance of learning of uninformed traders has been highlighted by O'Hara (2001): "*It is the uninformed traders who provide the liquidity to the informed, and so understanding their behaviors can provide substantial insight and intuition into the trading process*". Furthermore, O'Hara puts forward an open question on what traders can learn from other pieces of market data, such as prices. However, this question raised by O'Hara has not been fully explored since most of microstructure models focus on the behavior of informed traders, instead of uninformed traders (see the survey in Rosu, 2012). To address O'Hara's question, by assuming asymmetric and short-lived information as in Goettler et al. (2009), we consider a limit order market populated by informed traders who trade optimally on their private information about the fundamental values and uninformed traders who trade on their expected fundamental values estimated from order book and market information, including current mid-price of the bid and ask, the average historical market prices and lagged fundamental values.

Among various learning mechanisms, we introduce genetic algorithm (GA) with a classifier system as an adaptive learning mechanism

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for uninformed traders to tackle the challenges of learning in limit order markets. GA firstly introduced by Holland (1975) has been widely used in economics and financial markets.[1] It is a search heuristic that mimics the process of natural evolution, such as mutation, selection, and crossover. It generates optimal solutions to the changing environment. Apart from learning from experience, GA is spontaneous and creative (Chen et al., 2012). To make the learning more effective with the increasing number of states, the nature of dynamics, and complexity of limit order book, we introduce a classifier system based on order book and market information to facilitate the learning. The classifier system is a set of rules which contains a number of if–then or condition–action rules (Newell and Simon, 1972). It helps uninformed traders to classify a large number of market conditions in order to learn from both historical and current market data and to trade. The design of the classifier system is inspired by the SFI-ASM on a double auction market with a specialist, see Arthur et al. (1997), LeBaron et al. (1999) and Ehrentreich (2006). The classifier system has been introduced in a number of economic or finance models since 1990, such as Marimon et al. (1990) and Allen and Carroll (2001). GA with a classify system is then applied to evolve the classifier rules by discovering new rules and weeding out weak-old rules (Chen et al., 2012).

This paper is motivated by learning and strategic trading in financial market literature. To examine the effect of learning, we divide uninformed traders into GA traders who use GA learning to estimate their expected fundamental values for trading and randomly-behaving (RB) traders who do not learn and form their expected fundamental value randomly.[2] We extend the adaptive learning models in financial markets to a more general environment. By considering different learning abilities (some traders employs genetic programming learning) in a simplified double auction without order book, Yeh (2007, 2008) examines how the learning can affect price discovery and price volatility and highlights the importance of more general environment with market frictions, realistic trading mechanism, and coexistence of traders with different learning abilities. Easley et al. (2013) also point out that: "*[...] strategic trading behavior, executed by automated systems interacting directly with the exchange's double auction order book is more robust*". This paper incorporates many of these important features into a limit order market model, including asymmetric information, different learning abilities, and strategic trading among traders. We examine the effectiveness and value of the GA learning and its impact on the information value, information dissemination efficiency, order submission and liquidity in different market environment with different learning ability, volatility of the fundamental value, information lag and the number of informed traders. Our results provide some insights into understanding the algorithmic trading that shares many of these features.

This paper contributes to the literature in three aspects. *First, the learning is effective and valuable, improving information efficiency in the limit order market*. We first show that the GA learning is effective. It helps the GA traders to reduce their loss to informed traders and to increase profit from trading with the RB traders. The learning is also valuable with respect to information acquisition, forecasting, buy–sell decision accuracies, and profit opportunity for uninformed traders. Therefore when the information lag is long, the volatility of the fundamental value is high, or market fraction of the informed traders is low, learning improves GA traders' forecasting accuracy and therefore increases the value of the learning. Consequently, the learning improves information dissemination efficiency of the limit order market. The results contribute to the literature in that how efficient the adaptive learning performs in a limit order market. For example, without a classifier system, Kluger and McBride (2011) find that GA learning helps uninformed traders to coordinate in trading time, and Anufriev et al. (2013) find that GA learning makes traders improve market allocation; different from these two models, our model shows that the GA learning improves traders' price forecasting.

Second, learning reduces information value and hence whether traders pay to become informed depends on the trade-off between the value of learning and information cost. The values of learning and information increase in information lag and volatility (of the fundamental value) and decreases in market fraction of the informed traders in a limit order market. Put differently, information value is lower for uninformed traders with learning than without learning. This result has an important implication on information cost and acquisition. In an one-period agent-based equilibrium model, Hauser et al. (2015) find that with genetic programming learning, traders either pay the information with the highest information value to become informed traders or do not pay for any information to become uninformed traders when markets are not fully efficient but contain some noise to compensate informed traders' information cost. They further conjecture that if a market is efficient and uninformed traders cannot get superior information, uninformed traders should ignore all the available information and use passive trading strategies. This is because as long as a substantial share of market participants optimizes their strategies, processing incomplete and low-level information will not pay off. We show that in a dynamic limit order market, depending on whether uninformed traders learn or not, the information value can be different. It is more valuable for the uninformed traders without learning. Since the learning is more valuable, the GA traders would have less incentive to pay more than the RB traders to become informed traders. Therefore uninformed traders may not pay the highest information value to become informed when they learn (even in a less efficient market), depending on the trade-off between the value of the learning and information cost.

Third, the learning improves market liquidity supply. We show that with learning, both informed and uninformed traders submit more limit orders, while uninformed traders submit less market orders. Hence the learning increases liquidity supply. In the current market microstructure literature, to maintain analytical tractability, most of the limit order models focus on the order choice of informed traders and assume that uninformed traders' order submission is determined exogenously.[3] In this paper, instead of assuming exogenous order choice for the uninformed traders, the learning makes the order choice of the uninformed traders endogenously. It turns out that the learning has a significant impact on order submission behavior of both informed and uninformed traders. We show that in a similar information structure to Goettler et al. (2009), the learning of uninformed traders makes both informed and uninformed traders submit more limit orders and less market orders, hence increasing liquidity supply. This is different from Goettler et al. (2009) but consistent with Linnainmaa (2010). The results help to understand order submission behavior of informed and uninformed traders.

This model is built upon Wei et al. (2016) that focus on the stylized facts simultaneously in limit order markets. When information is asymmetric and short-lived and traders are randomly-behaving, Wei et al. (2016) reproduce a number of important stylized facts including fat tails and absence of autocorrelation in returns, volatility clustering, long memory in the bid–ask spread, and hump-shaped depth closer to the best quotes. More importantly, they find that the use of historical information by uninformed RB traders plays a unique role in explaining

[1] See, for some pioneer examples, Arifovic (1996), Arthur et al. (1997), Allen and Karjalainen (1999) and Routledge (1999).

[2] The RB traders act randomly. Difference from zero-intelligence agents, they use market information (to become clear late), see the survey of Chen (2012) for more detail discussions.

[3] For example, Goettler et al. (2009) assume that uninformed traders' order submission is mainly depended on the exogenous private value rather than asymmetric information and Rosu (2016) assumes that the uninformed traders' order submission is determined by the exogenous buy–sell decision and time preference. In Goettler et al. (2009), uninformed traders prefer to submit market orders to consume liquidity. However, using the same method in Goettler et al. (2009), Linnainmaa (2010) assumes that the traders with private value to be informed traders (such as institutional traders) and traders without private value to be uninformed traders (such as individual traders). He finds that uninformed traders provide liquidity to informed traders, consistent with the empirical finding.