On the Role of Intensive Search in Stock Markets: Simulations Based on Agent-Based Computational Modeling of Artificial Stock Markets

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1 Introduction

Based on the **agent-based artificial stock market** built by Chen and Yeh (2000), this paper study the effect of search intensity on the complex dynamics of artificial stock markets via the manipulation of *peer (social) pressure* function, i.e., the *rank function*.

2 Search

In Chen and Yeh (2000), the *rank function* plays a role in transmitting the *peer pressure* received by traders to their *search intensity.* By appropriately choosing a *rank function*, we can manipulate the sensitivity of traders' search intensity to peer pressure. For example, consider the following two types of rank functions, one is

$$p_{i,t} = (\frac{R_{i,t}}{N})^2, \tag{1}$$

called **Rank Function 1**, and the other is

$$p_{i,t} = (\frac{R_{i,t}}{N})^{\frac{1}{2}}, \tag{2}$$

called **Rank Function 2**.[1] Then since

$$0 < \frac{R_{i,t}}{N} \leq 1,$$

it is clear that Rank Function 2 shall make traders more sensitive to peer pressure and consequently search more actively, while Rank Function 1 would make traders a little sluggish in response to peer pressure.

Given this understanding, it is not surprising to see that the number of traders registering to the b-school would be much higher under Rank Function 2 than Rank Function 1, while how much the difference is is an empirical issue. Using *the AIE-ASM Version 2*, we simulate the artificial stock market by using the two rank functions as scenarios, each with 2000 trading days. Figure 1 exhibits the histograms of these numbers. When Rank Function 1 is employed, the average of these numbers is 325, while when Rank Function 2 is employed, the average comes up to 412. This difference is significant enough to confirm our priori expectations.

[1]These two rank functions are proposed by modifying the the linear function, Equation (23), in Chen and Yeh (2000).

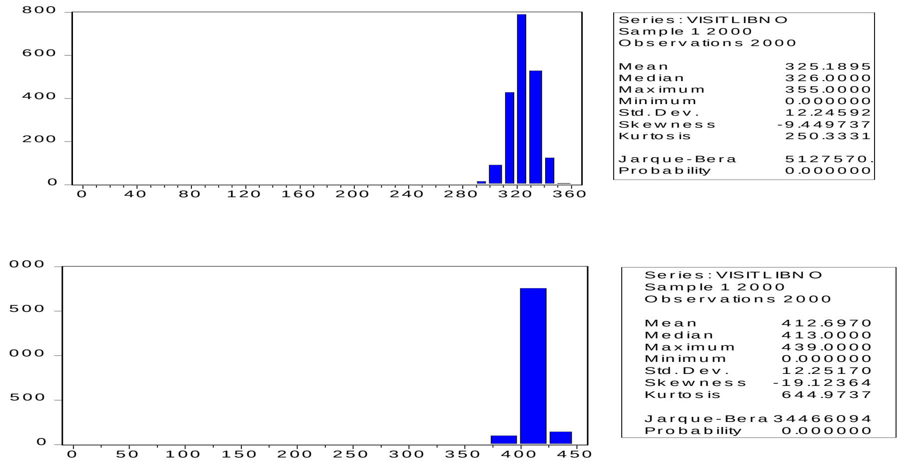

Figure 1: Histogram of the Number of Traders Registering to the B-School

The upper one is corresponding to the case of **Rank Function 1**, and the lower one is corresponding to the case of **RanK Function 2**. The right-hand side of each histogram is the basic statistics of the respective histogram.

However, what may make these experiments more interesting is to inquire whether the increase in search intensity, due to different employment of rank functions, can actually lead to some *real effects. First of all, would the increase in search intensity make the chance of successful search even more difficult?* While our intuition may suggest so, it is very difficult to have a hard proof. Therefore, here we examine the success ratio, $r_{s,t}$, defined as follows:

$$r_{s,t} = \frac{N_{2,t}}{N_{3,t}}, \tag{3}$$

where $N_{2,t}$ is the number of traders with successful search, and $N_{3,t}$ is the number of traders registering to the b-school at period t. The histogram of $r_{s,t}$ is given in Figure 4. From Figure 4, we can see that the average success ratio r_s for the case with more intensive search (Rank Function 2) is only 0.41, which is even smaller than the chance by even simply random guessing. However, this average is 0.503 in the case with less intensive search (Rank Function 1). Therefore, our intuition that *intensive search would make a successful search even harder* is also confirmed.

3 Heterogeneity

There is a slight evidence to support that the increase in search intensity could make the subjective expectations about the future more homogeneous. The upper half of Figure 5 gives the time series plot of the dispersion of subjective expectations. In the case of Rank Function 1 (the left one), the *median* of this dispersion statistics is 0.03. But, it is reduced down to 0.01 for the case of Rank Function 2 (the right one), which is about a third of that of the previous case. The impact of search intensity on heterogeneity of traders is also reflected on the dispersion of *share holding.* The lower half of Figure 5 is the time series plot of the dispersion of share holding among traders. The median of this dispersion is 0.003 in the case of Rank Function 1 (the left one), but then shrinks further down to 0.0009 in case of Rank Function 2 (the right one), which is *also* roughly a third of that of the previous case. Therefore, we may conclude that *increase in search intensity may reduce the degree of heterogeneity of traders.*

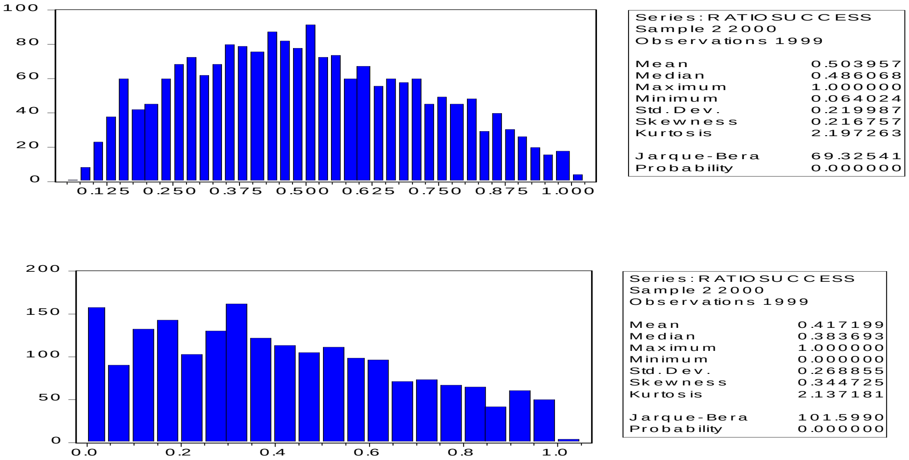

Figure 2: Histogram of the Ratio of Traders with Successful Search in the B-School

The upper one is corresponding to the case of **Rank Function 1**, and the lower one is corresponding to the case of **Rank Function 2**. The right-hand side of each histogram is the basic statistics of the respective histogram.

4 Collective Rationality

The third question to ask is whether increase in search intensity would make the *market expectations*, defined as *the average of all traders' expectations*, follow the true price and dividends closer. Figure 6 is the time series plot of the traders' expectations error and the associated statistics. The median of the market expectations' error for the first case is 0.83, which is much higher than the one in the second case, i.e., 0.13. In addition, it also has a higher skewness and kurtosis, while its volatility is slightly less. Therefore, there seems to have a real effect of intensive search on reducing market expectations' error.

5 Evolving Complexity

The other interesting aspect of simulating stock markets is to study whether traders' *perception* of the world tend to become more and more complex as time goes on. Since all forecasting models (traders' perception) are in the format of LISP trees, we can ask *how complex these forecasting models are.* To do so, we give two definitions of the *complexity* of a GP-tree. The first definition is based on the *number of nodes* appearing in the tree, while the second is based on the *depth* of the tree. On each trading day, we have a profile of the evolved GP-trees for 500 traders, $\{f_{i,t}\}$. The complexity of each tree is computed. Let $k_{i,t}$ be *the number of nodes* of the model $f_{i,t}$ and $\kappa_{i,t}$ be the *depth* of $f_{i,t}$. We then average as follows.

$$k_t = \frac{\sum_i^{500} k_{i,t}}{500}, \quad and \quad \kappa_t = \frac{\sum_i^{500} \kappa_{i,t}}{500}. \tag{4}$$

Figure 7 displays the evolving complexity in these two experiments. The upper half of the figure presents the mean complexity, i.e., k_t and κ_t, whereas the lower half of the figure gives the *variance* of the respective complexity. This figure seems to indicate that increase in search intensity can in effect not only reduce the evolving complexity of traders' perception, but also can reduce their diversity. This is well evidenced in the right half of Figure 7. In the case of Rank Function 2, we can see that the evolving complexity, while increasing at the very beginning, but quickly drops to a very low level and then stays there for the rest of the time. Associated with this change in trend, the dispersion of traders' perception actually comes down to nil. In other words, a collection of heterogeneous traders eventually evolve to a collection of homogeneous ones. But, none of these happens in the first market.

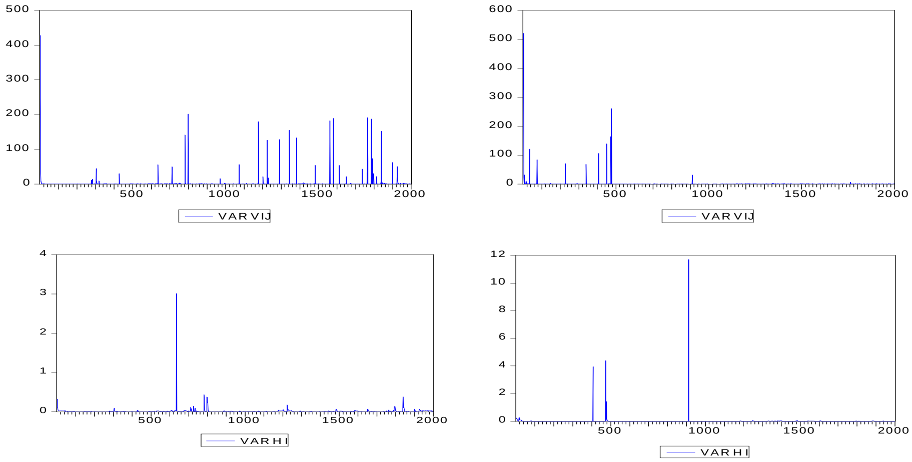

Figure 3: Time Series Plot of Dispersion of Subjective Expectations and Share Holdoing

Dispersion of subjective expectations is shown in the upper half of the Figure, whereas that of share holding is shown in the lower half of the Figure. The left ones are corresponding to the case of **Rank Function 1**, and the right ones are corresponding to the case of **Rank Function 2**.

References

[1] Chen, S.-H. and C.-H. Yeh (2000), "Evolving Traders and the Business School with Genetic Programming: A New Architecture of the Agent-Based Artificial Stock Market," *Journal of Economic Dynamics and Control*, forthcoming.

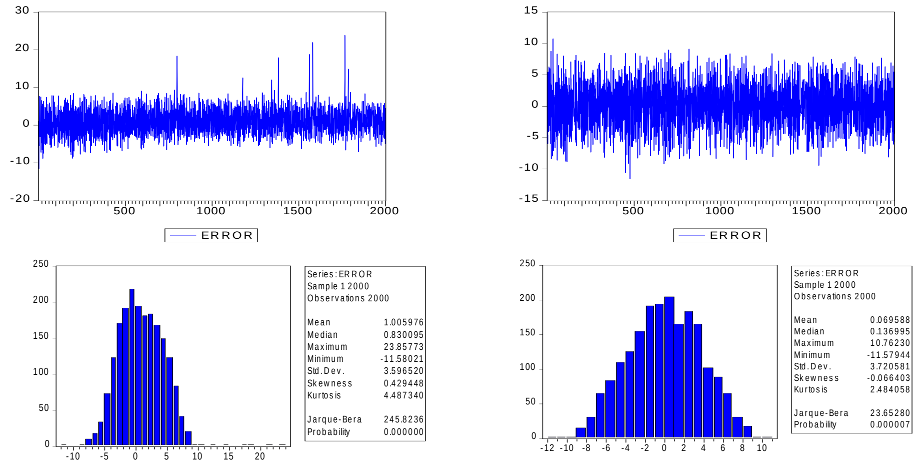

Figure 4: Time Series Plot and Histogram of Market Expectation's Error

The left ones are corresponding to the case of **Rank Function 1**, and the right ones are corresponding to the case of **Rank Function 2**.

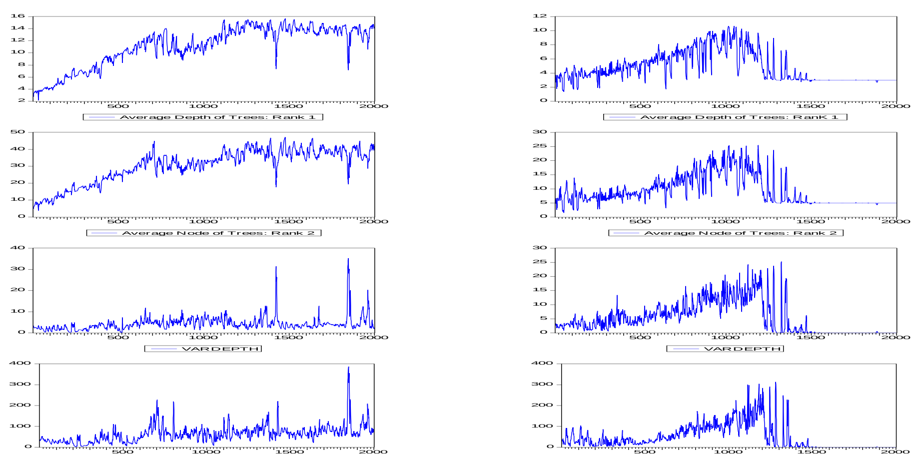

Figure 5: Time Series Plot of Evolving Complexity: Numbers of Depth and Node

The left ones are corresponding to the case of **Rank Function 1**, and the right ones are corresponding to the case of **Rank Function 2**.