Spring 2018 Complexity Challenge[*]

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1. Introduction

Economics has been a contested topic since humans started to trade goods and services with each other. Studying the history of economic thoughts enlightened us about the different approaches adopted over time to understand and optimise economic activities. For example, Traditional Neoclassical Economics assumes that economic decisions are made by entities that are perfectly rational, have complete knowledge of each other's strategies/plans, and can employ perfect deductive reasoning (Viale, 1992; O'Driscoll and Rizzo, 2002). This approach has been challenged by Complexity Economics which acknowledges that those entities do not usually act rationally (Arthur, 2014), not to mention that they tend to have limited information and a small amount of time to make decisions (Beinhocker, 2006). Arthur (1994) discuses these limitations in a paper dedicated to analysing what later became known as the *El Farol Bar problem*. He argues that the economic entities/agents usually seek boundedly rational solutions rather than the overall perfect solutions (Whitehead, 2008) that might not exist or be feasible in real-world situations.

I believe that the *Spring 2018 Complexity Challenge* has been launched as part of the recent endeavours to better understand economic activities and interactions. The Challenge basically describes a system that contains three pools with different potential investment returns, and individual agents that have to choose one of the pools to invest in in each time step. The system might have meta-agents that coordinate the behaviours of groups of individual agents. There is also a specific fee (i.e. tau) which the individual agents have to pay every time they switch from one pool to another.

2. Real-world Application

I took the decision to interpret the Challenge as modelling a virtual stock market where individual agents are the strategies implemented in the system. These individual strategies cover three potential approaches taken by the investors who might be (i) long-term investors who are only interested in the long-term gains and usually choose a pool and stay in it for many rounds, (ii) gamblers who depend on luck and keep moving between pools in a random or a semi-random pattern, and without relying on meaningful information in their decisions, and (iii) speculators who are also, like the previous group, predominantly risk-takers and focus on short-term investment, but they make their investment decisions based on relatively sophisticated observation and analysis of the system and available data. The strategies (i.e. agents) can be implemented either individually by, for example, individual investors or collectively by mutual funds (i.e.

[*] Acknowledgement: Some ideas presented here were inspired by the discussion on the Complexity Challenge's forum.

meta-agents) that combine a certain subset of strategies and then share the return, which has been earned by the subset, equally among the combined strategies. Individual agents can be clueless (i.e. have a passive strategy) only in a situation where the meta-agents take absolute power and directly control the movements of their subsets between the pools. A system full of such authoritarian meta-agents moves away from being a complex system to being more like a centralised system where consequential interactions often occur at the meta-level. Moreover, I chose to interpret the potential returns generated in the system as either fixed interests paid by, for example, a bond (i.e. stable pool) or dividends shared between the owners of a certain company's stocks (i.e. low pool and high pool). The main difference between the interests and dividends is that interests guarantee a fixed payment at the end of each round, whereas dividends contain a risk element and there is a real possibility (i.e. 50% for the low pool and 75% for the high pool) that owning certain stocks might not yield any outcome. Finally, I interpreted the switching fees (i.e. tau) as commissions sucked out of the system's wealth by stockbrokers who facilitate the buying and selling of stocks and bonds.

3. My Model

The rules of the Challenge do not allow agents to access information about the identity, movement and earnings of their fellow agents; which severely limits the options that can be used to approach the investment problem. One option would be by tackling the problem in a holistic way through calculating the sequential probabilities of the risk and payoff of every pool throughout the game. However, I chose to achieve my solution by employing a multistep approach. I started by building a NetLogo agent-based model (see figure 1) based on the rules of the Challenge and a number of intuitive ideas of the possible strategies which agents may adopt in order to maximise their own wealth. Then, I observed the model's simulation both at an individual level to assess the performance of each strategy, and from a bird's eye view to spot the emergent behaviours that arose from the system. Finally, I tried to use retroduction[1] to understand the mechanisms behind the different behaviours (both at the individual and aggregate levels) in the system or at least to design additional strategies that can take advantage of such behaviours. The model includes a total of 12 individual strategies and three meta-strategies. The individual strategies are explained in appendix 1, while the meta-strategies are discussed in the analysis section. The individual strategies can be categorised under the three strategy groups mentioned above (i.e. long-term investment, gambling and speculation). The model's code and generated data were subject to in-depth examination, and a number of debugging tests were undertaken. The findings below are mostly a result of analysing averaged data that were generated over a large number of runs; usually each run lasted for 100 rounds.

[1] Retroduction is a type of reasoning that conducts a historical induction of the events that occurred in the past (e.g. the historical pools' data) in order to find out the causes of those events (Veyne, 1984).

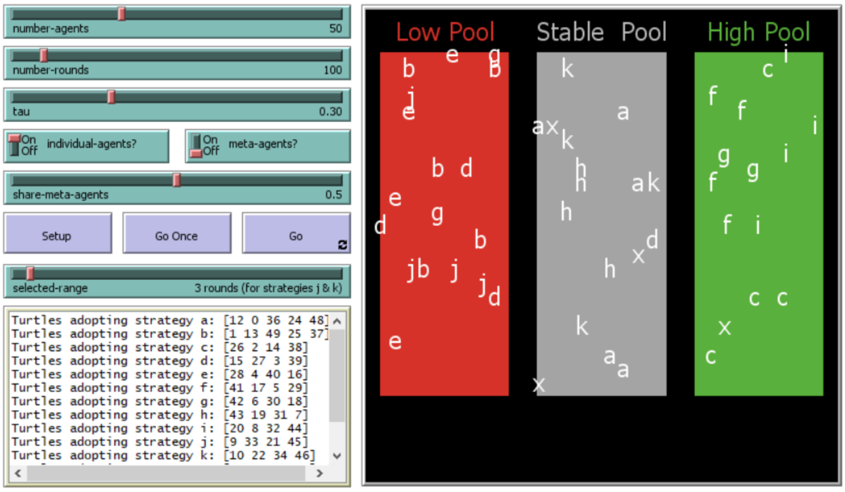


Figure 1

4. Analysis

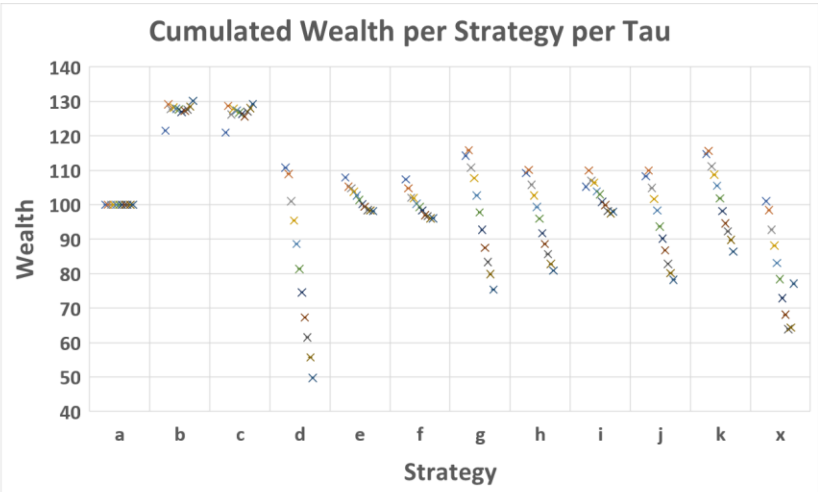
4.1 Characteristics of a Good Strategy

The question which I often asked while building and testing my model is *how can we measure the success of a strategy?* To answer this, I acknowledged that the Challenge resembles a competition game where cooperation or ‘greater good’ might not be considered by the players. Although cooperation could, in some cases, yield better results than competition for every single player (Rapoport *et al*., 1965), I took the decision to simplify the game and consider agents as selfish entities that are not willing to cooperate with others. This led to me adopting the strategy’s returns (payoffs after tau deducted) as a key standard to measure the strategy’s success. However, from my experience working on the Challenge, I came up with a number of characteristics that could increase the effectiveness of a strategy (see table 1):

Table 1: Characteristics of a Good Strategy

- Stability and Constancy: ability to provide reasonable performance which does not fluctuate significantly (important for strategies aiming at less risky activities in the short term).
- Profitability: ability to generate a high outcome over a number of rounds (might fluctuate a bit but the end result is desirable).
- Versatility: not requiring many pre-set parameters based on a pre-analysis of the system.
- Adaptivity: ability to evolve and/or make dramatic changes, if required, based on the emerging data during the game.
- Unpredictability: ability to prevent other players from predicting its next action.

Considering the first two characteristics (i.e. stability and constancy), I noticed that my Cautious Chaser Strategy (CCS) does well (see the solutions illustrated in figure 4 where CCS is represented by the red line) when it is operating in a system dominated by strategies which either have a constant behaviour (e.g. strategy a, strategy b and strategy c) or which depend on some sort of periodic analysis of the pools' data (e.g. strategy j and strategy k). This kind of strategies amplifies the periodic behaviours of the system and makes it easier for CCS to predict it. However, CCS's performance drops significantly after introducing additional strategies with more random movements. This also highlights the importance of the 'versatility' characteristic, given that the general behaviour of a system significantly depends on the operating strategies in that system. I anticipate that strategies which are weak in 'versatility' and those which are tailed to or trained for a certain environment might not do well in the Challenge's tournament when they face a totally different set of strategies than what they are used to compete against. Figure 2 shows another example of how strategies differ in their sensitivity to changes in the system's environment:



1000 runs for every 0.1 tau (from 0 to 1) - 11000 runs overall - each run lasts for 100 rounds
Strategy d is the most affected one by the changing in tau value; whereas strategy b and strategy c are the least affected ones by the changes in tau value, which makes sense as they do not switch pools (i.e. pay tau)

Figure 2

'Adaptivity' is another characteristic that my analyses found crucial in determining the success of a strategy. Figure 5 (left-hand graph), for instance, shows that when the number of agents in the system goes up and when the stable pool becomes the only viable option left to invest in, strategy x changes course to follow the trend represented by strategy a. In another case, I noticed that when allowing the model to run for a long time (e.g. 1000 rounds), the fluctuations of the wealth generated by the strategies are not broad enough to overcome the general trends of the strategies (see figure 3). Therefore, strategies with high adaptivity would perhaps use a linear regression technique to forecast future trends when the number of rounds increases sufficiently to make such forecasting accurate, whereas strategies with short memory or those which would not take into account long-run trends would be at a disadvantaged position in comparison to the first group of strategies.

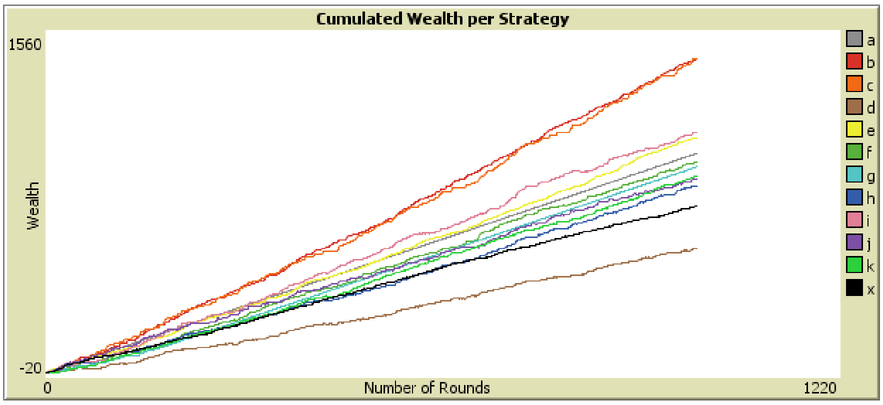
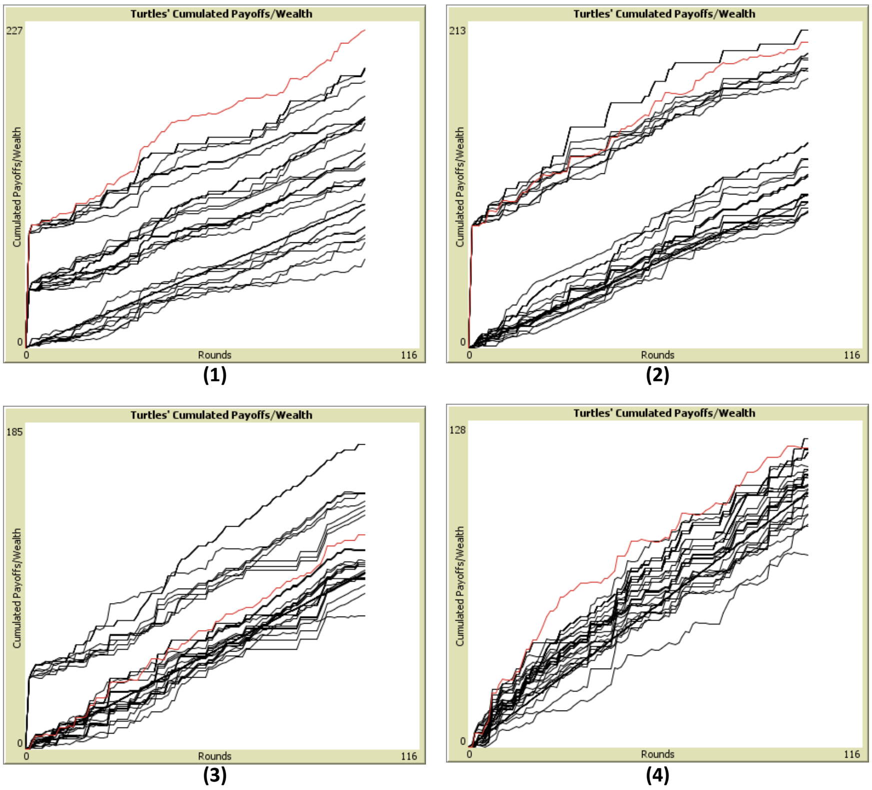


Figure 3

4.2 Emergent Behaviours in the System

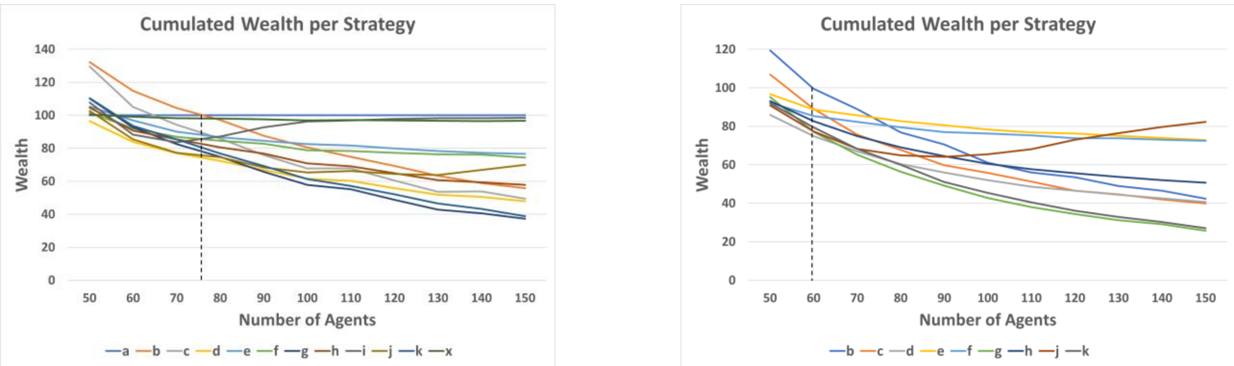
The performance of a strategy (i.e. how much wealth it accumulates) does not only depend on how well it translates the available information into accurate prediction and effective execution; it also depends on its luck at the start of the game when no information is yet available.



Graph 1: the returns of the stable, low and high pools in the first round are 1, 40 and 80, respectively.
Graph 2: the returns of the stable, low and high pools in the first round are 1, 0 and 80, respectively.
Graph 3: the returns of the stable, low and high pools in the first round are 1, 40 and 0, respectively.
Graph 4: the returns of the stable, low and high pools in the first round are 1, 0 and 0, respectively.

Figure 4

Figure 4 shows that the strategy represented by the red line, which always moves to the high pool at the start of each game, appears to perform well in every round. However, its high performance is not always sufficient to place it in the top of the agents' ranking, specifically in the case when the returns of high and low pools are 0 and 40, respectively (graph number 3). In other words, the success of a strategy might be dependent on the initial conditions, particularly when the system is not overpopulated; therefore, the first round(s) could be crucial in determining the winner of the game, as there is a high chance for a single strategy to receive high payoffs or low payoffs at the beginning of the game and before the system is stabilised when information becomes abnormally high and available to all strategies operating in the system. It is doubtful that this phenomenon highlighted in the simulation process can exist widely in real-world situations as the lack of information in the financial market is often substituted by, for example, adopting assumptions or creating imaginary stories about the various elements of the market (Tuckett and Nikolic, 2017). Furthermore, unlike my simulation model, the external factors (e.g. economic, social and cultural) are not isolated from the decision-making process of human agents.



100 runs for every 10 agents (from 50 to 150) - 1100 runs overall - each run lasts for 100 rounds

Figure 5

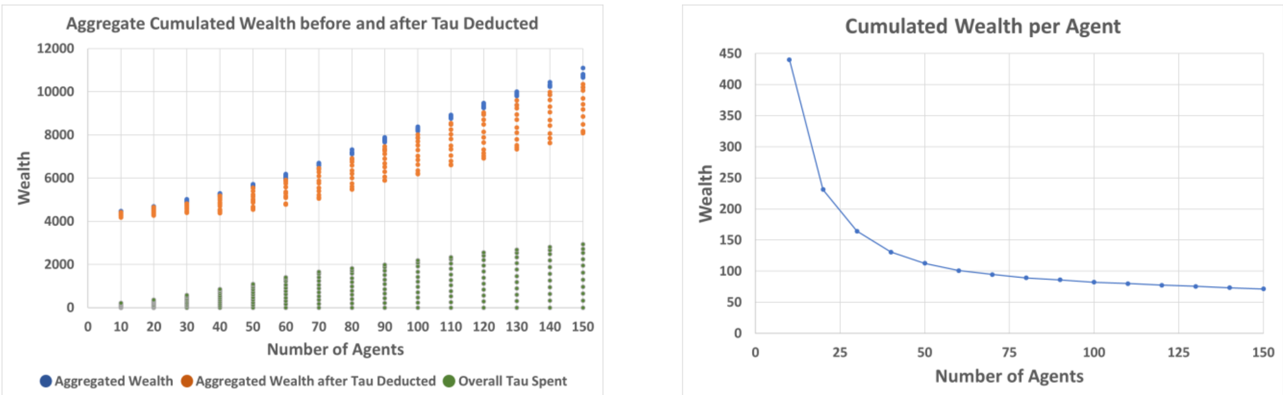
The number of active agents also plays a key role in shaping the emergent behaviour of the system. Mathematically speaking, it is more profitable for agents to invest in the stable pool when the system is most crowded, specifically after the number of agents in the system exceeds the threshold of 60 agents, assuming that agents are distributed equally between the three pools[2]. Figure 5 shows that the more the strategies in the system are focusing on the stable pool, the more the threshold slides further to the right; by excluding these strategies (i.e. strategy a, strategy i and strategy x) from the system, the threshold moves to the area around 60 agents (see figure 5; right-hand graph). Generally speaking, when the number of resident agents in the low pool exceeds 40 agents, the stable pool becomes more investable than the low pool in all

[2] 60/3 = 20 agents for each pool. Therefore, when the number of agents in the system is 60, the potential return per agent in each round is (80*0.25)/20= 1 for the high pool and (40*0.5)/20= 1 for the low pool. The higher the number of agents in the system is, the more settled the system becomes. This is because the high number of agents makes it very difficult for any gap to be missed. It would also neutralise the impact of the high and low pools (e.g. few agents sharing $80 reward in the high pool) and makes it more profitable to invest in the stable pool.

possible cases. Similarly, when the number of resident agents in the high pool exceeds 80 agents, the stable pool becomes more investable than the high pool in 100% of the cases (see figure 6).

Figure 6

Altering the tau as well as the number of agents operating in the system also affects the wealth share (i.e. wealth per agent). Figure 7 illustrates that, as the number of agents within the system increases, the aggregate cumulated wealth increases as well as the amount of tau paid; whereas the average accumulated wealth per agent decreases. Altering tau has a noticeable influence on reducing the amount of overall cumulated wealth that remains in the system, particularly as the number of agents increases; which can be attributed to the fact that the more agents there are operating in the system, the higher number of tau payments are made and the more wealth is sucked out the system into the stockbrokers' pockets.

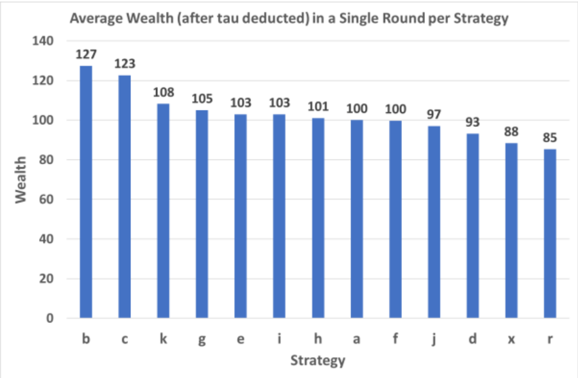


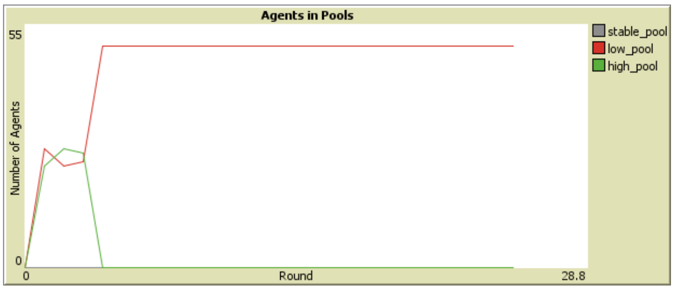
100 runs for every 0.1 tau (from 0 to 1) and 100 runs for every 10 agents (from 10 to 150) -16500 runs overall - each run lasts for 100 rounds

Figure 7

4.3 Availability of Information at Individual Level

A question might come to mind concerning what would happen if we relax the rules governing the system and allow agents to observe each other's behaviours. To explore this, I designed a new strategy "r" which uses the same idea adopted by the Cautious Chaser Strategy (CCS) to take advantage of any periodic behaviour that might emerge from the data gathered from each single agent. Surprisingly, the additional information provided about every individual agent in the system seems to have an opposite effect on the strategy's performance. It can be noticed from figure 8 that 'strategy r' achieves the poorest payoff for a single round. I also let strategy r operate by itself in the system and found that, as all the agents had the same strategy and knew each other's history, they all kept chasing each other; which made the system very inefficient (either all the agents occupied the low pool or they all located themselves in the high pool). The same phenomenon is also reported by Bell *et al.*(2003) who find that enabling agents to have access to full information does not necessarily yield better results.





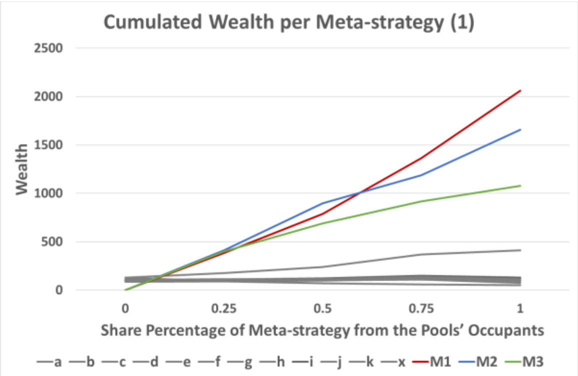
10000 runs overall - each run lasts for 100 rounds (left-hand graph)

Figure 8

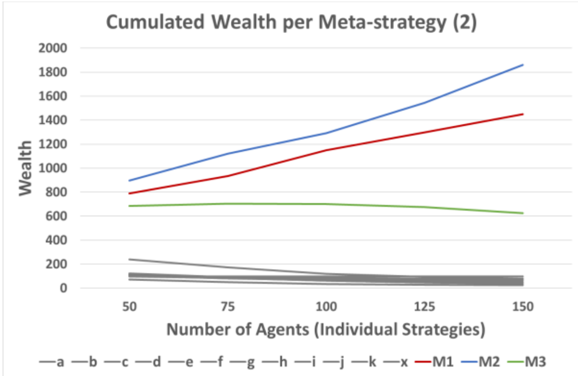
4.4 Meta-agents

I designed three meta-strategies which fall into two categories. The two meta-strategies in the first category combine a certain subset of individual strategies and then share the return, which has been earned by the subset, equally among the combined strategies. The first and second meta-strategies try, respectively, to (i) randomly combine a subset of my individual strategies, and (ii) combine a subset of strategy e and strategy f which are chosen randomly (50-50 chance) (see appendix 1 for more information about my individual strategies). The idea of the first meta-strategy is to try to discover an optimum set of combined individual strategies by using the 'trial and error' method. The second meta-strategy was designed to impose a monopoly on the system by trying to gain as much return as possible from the high and low pools, while also take advantage of the stable pool when the high and/or low pools become uninvestable. The second category only includes one authoritarian meta-strategy which takes absolute power and directly controls the movements of its sub-agents. It also tries to impose a monopoly on the system by directing its sub-agents to occupy the high pool every third round and occupy the low pool every fifth round.

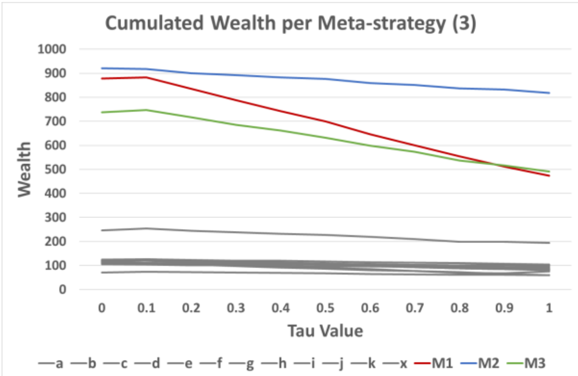
An analysis of the performance of the three meta-strategies concluded that the democratic met-strategies (i.e. M1 and M2 in the first category) always preform better than the authoritarian meta-strategy (i.e. M 3 in the second category) under different values of system share, number of agents and tau (see figure 9). This could be because the democratic meta-strategies have more diverse set of procedures and are able to exhaust more possibilities in their computational system than the authoritarian meta-strategy. In the case of one meta-agent or a number of cooperated meta-agents controlling the system, there would be a possibility for the meta-agent(s) to use the knowledge illustrated in figure 6 to maximise the wealth of the system, reduce the instances of switching pool and drive the stockbrokers out of the stock market. Further analysis should be conducted to examine whether the different individual strategies are better off (i.e. can accumulate more wealth) involving in a meta-strategy or acting alone.



5000 runs overall (1000 runs for each value in the horizontal axis)



5000 runs overall (1000 runs for each value in the horizontal axis)



11000 runs overall (1000 runs for each value in the horizontal axis)
Each run lasts for 100 rounds (for all three graphs above)

Figure 9

5. Conclusions and Future Research

Although scholars might have never intended to use agent-based modelling to capture the whole reality, it worth emphasising that the overly dependence on simulation models could be misleading if these models ignore, for example, the psychological and cultural factors that influence the human agents who are included in such models. Here, I strongly advise to consider the sociological and psychological literature when agent-based models are designed. For example, the Hofstede *et al*.'s (2010) dimension of 'long term orientation versus short term orientation' can be used in an agent-based model as one of the cultural factors that influence the decision-making of people. The case of potential interactions between human and AI agents in the stock market as well as the ability of different agents in my simulation model to enter and leave the stock market as they like could also be explored.

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Appendix 1: Individual Strategies Implemented in the Model

Category	Strategy
Long-term investment	Strategy a: only invest in the stable pool. Strategy b: only invest in the low pool. Strategy c: only invest in the high pool. Strategy e: only invest in the low pool and never move unless the sum of the payoffs earned from the low pool during the last five rounds is less than otherwise investing in the stable pool. The sum of payoffs (with tau deducted) is checked every five rounds. Strategy f: only invest in the high pool and never move unless the sum of the payoffs earned from the high pool during the last five rounds is less than otherwise investing in the stable pool. The sum of payoffs (with tau deducted) is checked every five rounds.
Gambling	Strategy d: move randomly between pools. Strategy g: move between the high and low pools until own wealth (payoffs with tau deducted) reaches $100 or more, then move to the stable pool and stay there. Strategy h: invest in the stable pool until $35 is earned, then move between the high and low pools while using the start-up saving to cover any later losses.
Speculation	Strategy i: choose the most profitable (per agent) pool so far. Strategy j: choose the most profitable (per agent) pool in the last selected-range (defined by a slider) rounds. Strategy k: choose the least profitable (per agent) pool in the last selected-range (defined by a slider) rounds. Strategy x: I name this the Cautious Chaser Strategy (CCS). I came up with this strategy by observing the cumulated wealth (payoffs with tau deducted) of some of the above strategies and by noticing that the graph lines representing the strategies' cumulated wealth often enter small-to-mid-range periods of accelerated increase followed by a decline. Therefore, I decided to use this inductive observation as a base to design a strategy that takes advantage of such periodic behaviours. The main objective of CCS is to generate synthetic data (based on the historical data of the pools) resembling the accumulated wealth of a number of chosen sub-strategies, and then use these data to decide which sub-strategy is most likely to achieve the steepest rise in the next round. The sub-strategies consist of (i) three unpaired strategies identical to strategy a, strategy b and strategy c above (i.e. invest in a specific pool during the whole game) and (ii) a further 18 strategies (nine pairs[3]) identical to strategy j and strategy k above, but with nine different selected ranges (i.e. 2-10). The slope of each of the sub-strategies' lines is calculated at three different points (for the last three rounds). Certain weighting is given to the slope values, and then all the three weighted values of each sub-strategy are added up to a final value stored in a solution list. In the comparing stage, the sub-strategy with the maximum value in the solution list is defined as the preferred strategy whose choice of upcoming move (i.e. chosen pool) is adopted. The tau values to be paid in the case of switching pool is also considered in the decision process. The name — Cautious Chaser Strategy — refers to the idea of chasing the sub-strategy (i.e. adopting its upcoming choice) which is more likely to have the steepest rise in the next round. The Cautious part was developed later by adding a code that directs investment into the stable pool if the standard CCS's computing has yielded undesirable payoffs (i.e. less than otherwise investing in the stable pool) within a specific period of time.

[3] The number of pairs was chosen arbitrarily, but it would be more appropriate if further testing was done to find out whether the width of the ranges from which the historical data are taken does actually affect the performance of CCS.