行政院國家科學委員會專題研究計畫 期末報告

不確定情況下重複決策問題之實驗研究

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中 文 摘 要 ： 多重賭博機問題，乃指決策者面對重複的多個不確定選項時，該如何作抉擇的問題。舉凡金融、商品、就業、財務管理等諸多面向的實際議題，皆可在多重賭博機問題的架構下進行探討。因此，研究者已投入相當多的努力來尋找適用於各種賭博機問題的最佳策略。然而，實驗經濟學的研究顯示出決策者的行為是偏離最適策略的。因此，近十幾年來已陸續有研究者透過真人實驗來探知人類在賭博機問題中的決策模式。

雖然實驗研究指出了人類在不同型態之博賭機問題中的行為特徵，甚至挑選出了最適合描述受測者行者的模型。但仔細縱覽系列文獻後可以察覺受測者的行為似乎與不同的實驗設計有關，而即使是在同樣的實驗設計中，研究者也發覺決策者似乎呈現不同的策略型態。因此，本研究從有限理性的角度出發，由決策者的內在條件(概念形成過程與認知能力限制）及外在環境條件(不同資訊集合與機率設計）兩個層面分別著手，試圖找出影響決策者策略型態的關鍵因素，並釐清其影響程度。

我們在多重賭博機問題的一個特殊版本－雙元預測問題實驗中，發現了受試者的確會在機率曖昧不明的情況嚴重不一的問題中傾向而採取不同的策略。而我們也實際選擇了雙方喊價市場作為一個測試實驗。在實驗中以固定但未知的交易者來模擬真實市場中交易者所遇到的不確定情況。因為真人受測者以外的交易程式是固定的，因此我們其實可以說各種不同出價所能帶來的收益是隨機的（取決於喊價時機），但又有幾個喊價值能為受測者帶來較高的利潤。因此我們的雙方喊價實驗實際上就是一個多重賭博機問題。實驗結果顯示受測者的行為的確呈現出一定的異質性，而個體的認知能力則對其行為與表現有顯著影響。

中文關鍵詞： 實驗經濟學，多重賭博機問題，雙元預測問題，雙方喊價市場，工作記憶，有限理性

英 文 摘 要 ： The multi-armed bandit problem is an abstract model that pictures a scenario in which agents have to repeatedly make choices among several alternatives whose payoff probabilities are unknown. Because of the lack of knowledge about the alternatives, agents have to learn the probabilities through experiences. However, due to the time or budget constraints, making decisions in multi-armed bandit problems always incurs opportunity costs. As a result, agents have to come up with a strategy to balance exploration and exploitation so as to maximize their total payoffs.

In this project, we first study how human subjects make decisions in a very simple version of multi-armed bandit problem. We found that subjects do behave heterogeneously when facing ambiguous alternatives. By varying the degree of ambiguity, subjects also demonstrates different styles of strategic behavior. We also examine the influence of human factors in subjects' decisions over time. With this knowledge, we moved to a more realistic problem where the ambiguity takes place in a market environment.

The second part of this research focuses on how human subjects make their market decisions when the behavior of other market participants is fixed but unknown. Following the logic of the first part, our goal is to examine whether human factors in terms of cognitive capacity can explain the differences in subjects market performance. To do this, we measure subjects' working memory capacity and let them trade in double auctions. In the experiments, subjects have to maximize their profits in a market where other traders are truthful bidding agents. Our results show that working memory capacity plays an important role in explaining subjects' market performance in most cases. However, there are evidence showing that other factors such as learning and experiences could also play a role. The market environment, with attributes different in many aspects, is crucial when one tries to assess the potential effects of cognitive capacity on subjects' market performance.

英文關鍵詞： experimental economics, multi-armed bandit problem, binary prediction, double auction markets, working memory, bounded rationality

An Experimental Investigation of Recurrent Human Decisions under Uncertainty

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Abstract. The multi-armed bandit problem is an abstract model that pictures a scenario in which agents have to repeatedly make choices among several alternatives whose payoff probabilities are unknown. Because of the lack of knowledge about the alternatives, agents have to learn the probabilities through experiences. However, due to the time or budget constraints, making decisions in multi-armed bandit problems always incurs opportunity costs. As a result, agents have to come up with a strategy to balance exploration and exploitation so as to maximize their total payoffs.

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Keywords: experimental economics, multi-armed bandit problem, binary prediction, double auction markets, working memory, bounded rationality.

1 Introduction

Many practical problems people encounter involve a series of choices in a repeated fashion. In these problems, agents have to choose among several uncertain alternatives about which they have little information. However, information is usually not given in advance but has to be collected only through the choices made by agents.

The *two-armed bandit* problem, or more generally, the *multi-armed bandit* or *N-armed bandit* problem, has been identified as an appropriate underlying model to describe such trade-off problems mentioned above. There are already a pile of studies which focusd on the normative properties of optimal strategies in various kinds of multi-armed bandit problems. However, not much has been done to study this issue in the experimental literature.

In fact, psychologists had already paid attention to this problem for a very long time. Binary prediction problem, which is a special case of the multi-armed bandit problem, has been investigated since the 1950s (Foulkes, 1959, Shepard & Chang, 1963, Tversky & Edwards, 1966, Feldman & Hanna, 1966, and Williams, Hartley, Taylor, & Harrington, 1975). In a binary prediction problem, there are two alternatives for each round of choice. In each round, one of the alternatives will be the correct answer. That is, the binary prediction problem is simply a special case of multi-armed bandit problem, in which the probabilities of the two alternatives add up to one in each round.

Although this issue has been studies by psychologist for a long time, most of their effort was focused on finding out what kind of patterns are used by subjects to predict a random event. Not much has been done to investigate subjects' strategies under different probability arrangements and the heterogeneity among subjects' strategies. In the first part of this project, we aimed to answer this question by conducting a series of binary prediction problems. By varying the probabilities of the winning alternatives, we manipulated the degree of ambiguity of this problem and observed how human subjects coped with those tasks.

In recent years, a few psychological studies has been devoted to this problem with a different point of view. West & Stanovich (2003) used questionnaires to investigate what kind of strategies human subjects would use in the binary prediction task. They provided subjects five different kinds of strategies in the questionnaire: Maximizing Behavior, Probability Matching, Gambler's Fallacy–Intuition, Gambler's Fallacy–Almost, and Gambler's Fallacy–Pure. The most striking findings in West & Stanovich (2003) is that male participants were significantly more likely to select the optimal Maximizing strategy than were the female participants. Later, Rakow, Newell, & Zougkou (2010) also studied how personal factors influence their performance in the binary prediction task. They found that participants with higher cognitive capacity were more likely to adopt the maximising behavior. Motivated by their study, we want to know not only if people's ability to handle repeated decisions under undertainty is different, but also the factors that cause such inequality. The second part of this project was devoted to study whether cognitive capacity, more specifically, working memory capacity, plays an influential role in subjects' ability to handle uncertainty in a market environment.

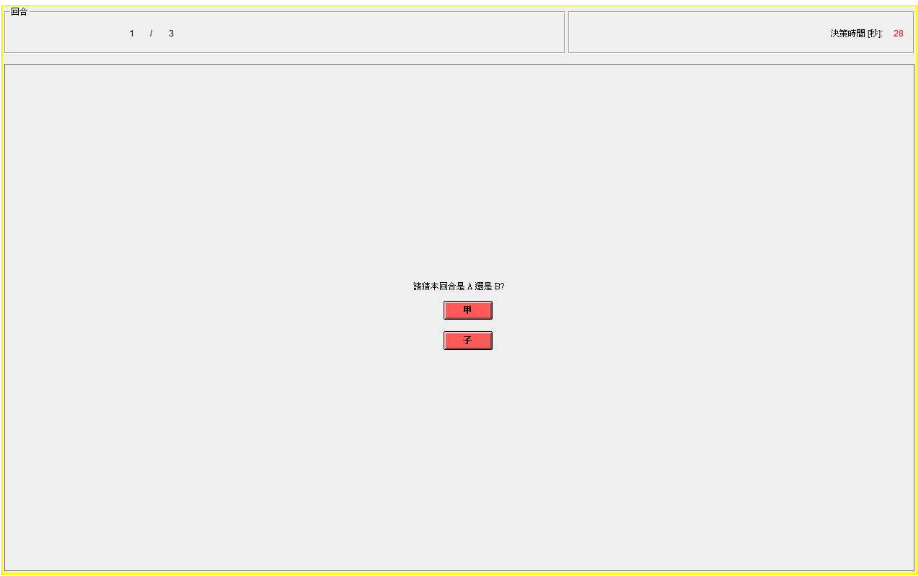

Fig. 1. Screen shot of the choice stage in the binary prediction task

2 PART I: The Binary Prediction Task

In the binary prediction task, we employed the simplest design as possible, but we varied the probability arrangements so that we can control the degree of the ambiguity.

2.1 Experimental Design

In each round of the experiment, subjects have to choose between two alternatives: the character "Chia" in the ten Heavenly Stems in Chinese (Tian Gan) and the character "Tzu" in the twelve Earthly Branches (Di Zhi). In each round, only one of the two alternatives is correct. The experiment last for 100 round, and in each round the computer randomly picks up a character as the correct answer.

The experiment is implemented in z-Tree (Zurich Toolbox for Ready-made Economic Experiments), which is proposed by Fischbacher (2007). In each round, subjects saw a simple choice screen like Fig. 1.

After subjects made their decisions in each round, they would immediately observe whether they had chosen the right alternatives, just like what can be seen in Fig. 2.

The probability arrangements used in our experiments can be summarized in Table 1.

Fig. 2. Screen shot of the result demonstration stage in the binary prediction task

After the binary prediction task, we asked the subjects to fill out a series of questionnaires. The questions in the questionnaire are simply the Chinese version of the questions asked in West & Stanovich (2003). We want to verified whether subjects' behavior really matched the answers they provided in hypothetical questions.

2.2 Results and Analysis

We totally received 135 subjects in the first part of this project. The gender distribution of male vs. female is 47:53. This information will be used to verify

Table 1. Probability Arrangements of Binary Prediction Tasks

Treatments	Probability of "Chia" versus "Zhu"	Number of Subjects
Experiment 1	40:60	29
Experiment 2	70:30	37
Experiment 3	55:45	34
Experiment 4	70:30	25
Experiment 5	55:45	20

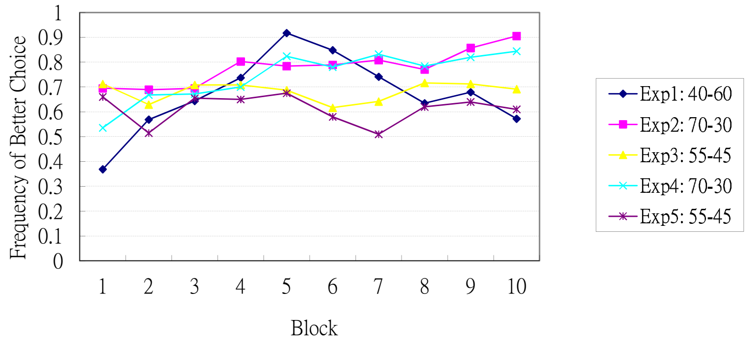

Fig. 3. Frequency of choosing the better alternative.

West & Stanovich (2003)'s findings of gender differences in behavior. We want to answer the following three big questions:

1. Will subjects' behavior change when the degree of ambiguity changes?
2. Is there a gender effect like what was observed in West & Stanovich (2003)'s study?
3. Can subjects' strategies be understood simply by ask hypothetical questions as in West & Stanovich (2003)'s study?

We will demonstrate what we have learned from our subjects in the following subsections.

Degree of Ambiguity With our five treatments, we can actually manipulate the degree of ambiguity that subjects faced during the experiments. Exp 2 and 4, where the probability arrangement is 70:30, constitutes the least ambiguous environment where subjects were expected to identify which alternative has a higher probability in winning more easily. Meanwhile, Exp 3 and 5, where the probability arrangement is 55:45, should confuse subjects more and make it difficult for them to identify the better alternative in a short time. Figure 3 demonstrate the results of subjects' behavior over time. In Fig. 3, we plot the average frequency of subjects' who choose the alternative with higher winning probability for each block (10 rounds). It is obvious that in Exp 2 and 4, subjects seem to learn over time and therefore there is a convergence in their behavior. On the other hand, in Exp 3 and 5, subjects have lower average frequency and do not exhibit any learning trend. The average behavior in Exp 1 is somewhat mysterious, it hits its top in the middle of the experiment, meaning that our subjects could learn, but then drops to a low level at the end of the experiment. The confusing behavior in Exp 1 reminds us that we cannot jump to the conclusion without more concrete evidence.

To yield a more reliable comparison among treatments, we first measure subjects' behavior from the middle of the experiment, that is, from round 51 to 100.

By doing so we can focus on whether subjects learned the better alternative or not. We also devised two quantitative measures to access their diverse behavior–namely AOA and AXB. AOA calculates the relative frequency of choosing the better alternative in the next round if they chose the better alternative and won in the current round. AXB, on the other hand, measure the relative frequency of choosing the worse alternative if they chose the better one but failed. If a subject has the knowledge of which alternative is the better one, and if he/she uses the maximizing strategy, his/her AOA would be exactly 1 and AXB would be zero.

Figure 4 demonstrates these indices for our five treatments. Exp 1 (40:60) on the top row; Exp 2 and 4 (70:30) in the middle row; Exp 3 and 5 (55:45) in the bottom row. It is obvious from Fig. 4 that the distribution of subjects' behavior in experiments with less ambiguity exhibits a higher centrality to the upper-left corner, while the distributions are more dispersed in experiments with high ambiguity. The behavior of our subjects roughly meets our expectation.

Gender Effects We also want to know whether gender is such an important factor dominating subjects' behavior as found in West & Stanovich (2003). It turns out that our results do not suggest any difference between males and females, no matter how we measure their behavior. We tried to compare their answers in the questionnaire, subjective categorizations of the time series of subjects' relative frequency of choosing the better alternatives, and even the AOA and AXB indices. No evidence is shown to support the assertion that male and female subjects adopt different strategies. This observation leads us to question whether West & Stanovich (2003)'s research method is reliable or not, and we will report our analysis for this issue in the following subsection.

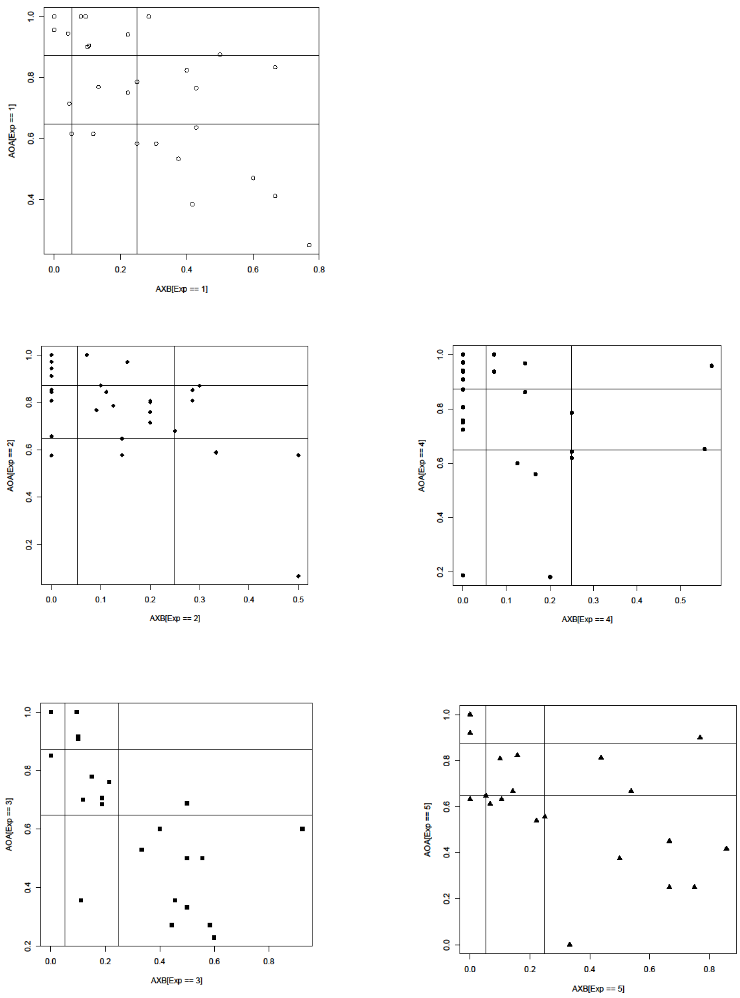

Fig. 4. AOA and AXB of round 51 to 100.

The Validity of Hypothetical Questions West & Stanovich (2003) used questionnaires to ask subjects what kind of strategies they would use when facing the binary prediction task. They found that males and females behaved quite differently by choosing different kinds of strategies–male subjects tend to choose the maximizing behavior once they have a sense of which alternative is better, while female subjects like to make their decisions according to instantaneous development. Because we let subjects to play the task by themselves and did not find similar evidence, we are quite doubtful about whether their research method can effectively reflect what subjects would really do in real tasks.

To evaluate whether answers in the questionnaire can truly reflect one's behavior in real tasks, we compare subjects' behavior and their answers in the questionnaire after the task. We categorize subjects' behavior by manually identify subjects' strategies–maximizing behavior, matching probability, or gambler's fallacy. We further compare the distributions of these strategies with the distributions collected from the questionnaire, and we found no evidence showing there is any consistent correlation between these two distributions. We also compare individually subjects' behavior and their answers. Also, no clear patterns were observed. Therefore, we seriously doubt that using questionnaires and ask subjects directly about their strategies before they have any experience in the task can yield meaningful data for analysis.

3 PART II: Heterogeneity in the Ability to Make Decisions under Uncertainty

Vilfredo Pareto, who is well-known for his study in income and wealth distribution, in speculating about the cause of economic inequalities, submitted the notion of *social heterogeneity*:

> "Human society is not homogenous; it is made up of elements which differ more or less, not only according to the very obvious characteristics such as sex, age, physical strength, health, etc., but also according to less observable, but no less important, characteristics such as intellectual qualities, morals, diligence, courage, etc." (Pareto, 1971, Chap II, 102)

Regarding the linkage between social heterogeneity and economic inequality, Pareto further asserted that:

> "To these inequalities of human beings per se correspond economic and social inequalities, which we observe among all peoples, from the most ancient times to the present, everywhere in the world, and such that this characteristic is always present." (Pareto, 1971, Chap VII, 2)

In the second part of this project, we are going to focus on one of the factors Pareto has pointed out: the *intellectual qualities*.

Instead of seeking institutional explanations for economic inequality, after Pareto, examining the influences of individual ability on economic performance has also become an attractive issue for economists for a long time. A large part of the interests focus on the influences of individual ability on income distribution, while recent research starts to look at other portion of economic activities, namely, behavior in investing activities, behavior in games, and behavior in market transactions. We will briefly go through them in the following sections.

3.1 Empirical Research of Cognitive Ability on Economic Outcomes

Economists' interests in individual ability on explaining income dispersion can be traced back to the nineteenth century, when Ammon (1895) compared the distribution of abilities, which was drawn from Galton (1869), with the distribution of incomes and pondered the relationship between one's ability and the income he/she receives. Later studies such as Moore (1911) and Staehle (1943) followed this trend by directly comparing the distributions of individual ability and income.

With the advancement of economists' statistical skills and the rich data provided by large-scale surveys, studies such as Murnane, Willett, & Levy (1995), Cawley, Conneely, Heckman, & Vytlacil (1997) Cawley, Heckman, & Vytlacil (2001), Zax & Rees (2002), Gould (2005), and Heckman, Stixrud, & Urzua (2006) are able to estimate how much cognitive ability contribute to the variations in wages, although some studies found that cognitive ability might not be the most important factor.

We have seen that cognitive ability do have certain influence on wages. However, job compensation is only part of people's economic activities. Investing behavior in financial markets is another important ways of cumulating wealth. Therefore, whether people with different levels of cognitive ability behave differently in terms of financial investment is another interesting question to ask.

Recently, Christelis, Jappelli, & Padula (2010) and Grinblatt, Keloharju, & Linnainmaa (2011) conduct empirical analysis to answer the question posted above. By investigating people's cognitive ability and their financial portfolios, both of them found that people with high cognitive ability invest more in stock markets. This finding is important because in their research, other demographic variables have been controlled, and there is even evidence that the effect of IQ on stock market participation is greater than that of income.

3.2 Experimental Investigation of Cognitive Capacity in Economic Behavior

The interests of using controlled experiments to study the effects of cognitive capacity on economic behavior, either by economists or psychologists, starts with the classical problem of Prisoner's Dilemma. Segal & Hershberger (1999) and Jones (2008) both hired subjects to run repeated prisoners' dilemma games. Segal & Hershberger (1999) found that higher IQ were associated with increased mutual cooperation, and Jones (2008) found that subjects cooperate more often by 5–8% whenever their SAT (Scholastic Aptitude Test) scores are 100 points higher.

Another group of the literature has posted a slightly different question. Instead of asking whether cognitive capacity influence our behavior, they ask further: how does cognitive capacity influence our choices? Burks, Carpenter, Goette, & Rustichini (2009) discover that in a sequential Prisoner's Dilemma game, subjects with higher IQ can predict the their opponents' behavior more accurately, be they the first movers or the second movers. Likewise, Devetag & Warglien (2003) employed various kinds of game context and found that the larger the subjects' short-term memory, the closer their decisions are to the rational choices. This is an interesting results, however, the most inspiring finding comes from their later work. Devetag & Warglien (2008) use a dedicated design to test whether subject "misunderstand" the game before they proceed to make their decisions. The results intriguingly subvert one's expectations–for some complex games, subjects with less short-term memory tend to misrepresent the games more and act *rationally* upon these "simplified" games.

Devetag & Warglien (2008)'s study raises another issue, which says that the effects of cognitive capacity will be pronounced in some games, while it could be obscurer in other games. This issue is important because it suggests that the assertion that social heterogeneity induces economic inequality can be supported or refuted at different levels of our economic life.

3.3 Cognitive Ability and Market Performance

It is natural to ask, after reviewing similar questions in various domains mentioned above, whether *inequality in agent's market performance can be attributed to the heterogeneity of their cognitive capacity.* Surprisingly, little has been done to seek a formal answer. To our best knowledge, Casari, Ham, & Kagel (2007) might be the closest effort for this question. By comparing subjects' actual bids to the theoretical break-even bids, Casari, Ham, & Kagel (2007) examined whether subjects suffer the winner's curse in common value auctions. They found that those whose SAT/ACT (American College Test) scores are below the median are more susceptible to the winner's curse.

Although Casari, Ham, & Kagel (2007)'s findings are valuable, we are more interested in private value auctions, which are the core mechanisms of a broad class of markets and therefore constitute our daily economic lives. We want to know whether our inherent cognitive capacity has already determined the benefit we can elicit from mutual exchanges.

The second part of this study aims to answer this important but neglected question using controlled experiments. By conducting individual-based market experiments where each human subject trade against computer agents, we are able to better control the factors influencing subjects' performance and therefore identify the effects of cognitive capacity with higher confidence.[1] Furthermore, by employing a formal psychometric measurement of cognitive capacity, that is, *working memory capacity* (WMC), we hope that the analytical results reported

[1] In our auction experiments, the true value of the commodity is known, so there is no judgement bias influencing subject's profits like in Casari, Ham, & Kagel (2007).

in this study can inspire advanced exploration of the behavioral foundations of economic inequality.

The plan of this article is as follows. Section 3.4 introduces our experimental design and procedures. Section 3.5 presents the results and analysis for the experiment, where truth telling agents are hired to accompany human subjects.

3.4 Experimental Design and Procedures

Our experimental designs can be summarized as two features: the individual market experiments and a formal psychometric test. The design of individual market experiments aims at removing the complicated and unknown influences of human strategic interactions, and focus only on the possible effects from individual's cognitive capacity.[2] The employment of a formal psychometric test is an effort to extract the most decisive component of cognitive capacity in relation to economic decision making. In this section, we will introduce how we achieve the above goals through a series of designs.

The Auction Markets In our auction experiments, each market consists of eight traders–four buyers and four sellers. Following the design of Rust, Miller, and Palmer (1993, 1994), each trader is endowed with four tokens.[3] As a result, there will be sixteen buyer tokens and sixteen seller tokens in the market. These buyer and seller tokens construct the demand and supply curves of the market.[4] Figure 5 illustrates the three market arrangements used in our experiments. These markets differ in their trading opportunities as well as the potential surplus for buyers and sellers.[5]

Referring to Fig. 5, first, every market has different amount of trading opportunities. The number of intra-marginal tokens each trader has in M1, M2, and M3 are two, one, and three, respectively. The differences in trading opportunities make profitability in each market different from each other. Let's focus on M3 first. M3 is probably the most friendly trading environment because each trader has three chances to make profits. In this situation, even if the subject misses

[2] One may argue that in real situations, people interact with each other and if the potential effects of cognitive capacity worth any discussion, we should take this complicated interaction into account in our experiments. However, this present study is focusing on extract general patterns from a very limited number of subjects. If human interactions are allowed, too many factors will be involved and the worry is that we may not be able to clarify their effects unless we have a very large sample.

[3] For buyers, the token values can be viewed as their reservation prices. For sellers, the token values can be viewed as the marginal costs of each item.

[4] Each trader's four tokens are evenly distributed along the demand or supply curve. In Market 1, for example, only eight out of sixteen pairs of tokens can make transactions. As a result, every trader in Market 1 will have two units bought (sold) if everyone bids/asks according to their token values.

[5] We can see that Market 1 and Market 2 are not completely symmetric. As a result, Market 1 and Market 2 might be more beneficial for sellers, while buyers and sellers have completely the same opportunity in Market 3.

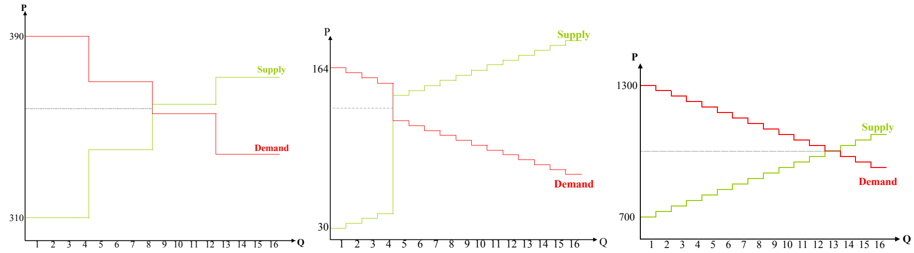

Fig. 5. Demand and supply schedules for the auction experiments. From the left to the right are Market 1 (M1), Market 2 (M2), and Market 3 (M3), respectively.

the first few delicious tokens from the other side of the market, he/she can still make it up later and make certain amount of profits. This easiness, however, does not exist in M2, where each subject has only one intra-marginal token. If the subject make a mistake by allowing his/her competitor to steal a trade with an extra-marginal token, then he will earn nothing but losing his only chance to trade. By the same intuition, one may expect the hardness of M1 lies between M2 and M3, i.e., M2 is harder than M1, and M1 is harder than M3.

Each subject was assigned as one of the eight traders in the market, and he/she would keep playing that role throughout the experiments.[6] Every human subject was accompanied by seven computerized trading agents in our experiments, and they were told so at the beginning of the experiments. The reason why we let human subjects compete with computer agents is that we not only can avoid other factors such as social preferences to influence their decisions during the experiments, but we can also simplify the analysis because we have full knowledge about computer agents' behavior.

Subjects will play the auction experiments following the sequence of Market 1 (M1), Market 2 (M2), and Market 3 (M3). Each market has six periods, and each period consists of twenty-five trading steps. In sum, subjects have to repeat the 25-step trading competition six times for each market structure before proceeding to the next market. We only inform subjects their own token values, and subjects can judge from the market information how many traders are there in the market (see Figure 11 in Appendix B).

During the experiments, we reveal past history of every trader's bids/asks and market prices on the screen.[7] Figure 11 in Appendix B demonstrates the information-revealing policy of our experiments. We provide past history because we don't want our subjects struggling with little clues during decision making plus the fact that traders in real situations often have access to such data if they want to. What we want to test here is not whether subjects can make better

[6] For example, once a subject was assigned as the second seller in the market, he/she will keep playing the role of the second seller throughout the three markets.

[7] Current bid/ask decisions will not be revealed. Only past data is presented on the screen.

decision because they can memorize more data, but to test whether they achieve different decisions due to the differences in their capability to manipulate the data. However, to better control the experiments, *no decision support utility such as paper and pencil or a calculator is allowed.*

The Auction Process We adopt discrete-time double auction is our experiments. Each trading period consists of twenty-five trading steps, and each trader can choose to bid/ask or pass in each step. In each trading step, the buyer who has the highest bid (the current buyer) and the seller (the current seller) who has the lowest ask have the opportunity to reach a transaction.[8] If the current buyer's bid (the current bid) is higher than current seller's ask (the current ask), a transaction takes place and the price is the average of the bid and ask. If the current bid is lower than the current ask, nothing happens and the auction will proceed to the next trading step.

Notice there are two importance features of our auction rule. First, speed is not important because in each step we only determine who are the current buyer and seller after we receiving all the decisions from traders. This fact prevents our subjects to be outperformed by computer agents simply because of the differences in their decision and action time. Second, the price is the mean of the current bid and the current ask. Again, it doesn't matter who send his/her order to the market first in the same step. However, timing is important because, for example, if a buyer wants to match a seller who offers a low price, he/she will have to provide a decent price in a early step otherwise that seller could reach a trade with other buyers.

Traders' bids or asks are not constrained by their token values, but their profits are calculated by the differences between the transaction prices and their token values. A buyer's profit is defined as his/her token value minus the transaction price; a seller's profit is defined as the transaction price minus his/her token value.

The Trading Agents In order to create a uncertain but fixed market environment for our human subjects, we want human subjects to experience the simplest market environment as possible. A kind of computer agent named *truth tellers* are therefore used. A truth teller will always bid/ask according to its token values, that is to say, it does not adapt to market situations and will keep the same behavior from period to period.

Before the experiment, we made it very clear to the subjects that they were going to compete with computer agents instead of other subjects in the laboratory. However, we did not reveal any further information about the agents we used.

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[8] If there is a tie between traders, the system will randomly choose one as the current buyer/seller.

The Measurement of Performance As mentioned earlier, we want to examine whether cognitive capacity has a general impact on human subjects' market performance. For this purpose, we not only have three different market structures but also place our human subjects in different positions in the markets. Nevertheless, these two arrangements make it difficult to evaluate subjects' performance since the opportunities vary across market structures and traders' market positions. To overcome this problem, we do not measure subjects' performance from raw profits but use a performance index instead to evaluate their success in the markets.

The performance index we used in this paper is defined as

$$\frac{\text{The actual profit earned}}{\text{The potential profit}} \times 100 \tag{1}$$

The potential profit is what a trader may earn for his/her tokens if *everyone* in the market bids and asks exactly according to their token values. Defined in this way, the performance index measures the ability of a trader to earn extra profits. An index larger than 100 means the trader manages to come up with a strategy which is better than truthfully bidding/asking in the markets. On the contrary, traders may have performance indices smaller than 100, and even negative numbers if they incur losses. In what follows, when referring to subject's "profit" we actually means "performance index".

Working Memory Capacity There are many options for researchers to assess subjects' cognitive capacity. In the present study, we choose *working memory capacity* (WMC) instead of using a general IQ or other test scores (such as SAT scores) because working memory capacity is not simply a measurement of the capacity of short-term memory, but a "conceptual ragbag for everything that is needed for successful reasoning, decision making, and action planning" (Oberauer, Süß, Wilhelm, & Wittmann, 2003).

To be more precise, Oberauer, Süß, Schulze, Wilhelm, & Wittmann (2000) summarized the functions of WMC as follows: (1) *storage and transformation*–how people simultaneously process and store information, (2) *supervision*–how humans monitor and control ongoing mental operations and actions, including selectively activating relevant representations and processes and inhibiting irrelevant ones, and (3) *coordination*–how humans coordinate information elements into structures. We believe these functions are quite close to what happens in people's minds when are making economic decisions.

The WMC test battery we used is proposed by Lewandowsky, Oberauer, Yang, & Ecker (2010). The test consists of five different tasks: backward digit span (BDG), memory updating (MU), operation span (OS), sentence span (SS), and spatial short-term memory (SSTM). Each of them measures a specific facet of the working memory capacity. The WMC score is obtained by normalizing the scores of the five tasks first and then taking the average of them.

The Experimental Procedures Both the experiments and WMC tests were computer-based. The double auction environment and the computerized trading agents were programmed using Java, while the WMC test run in Matlab with psychtoolbox.

At the beginning the experiments, subjects were asked to be seated and their roles in the markets were determined by the computers they used. We setup the computers according to the Latin Square Design so as to have our subjects distributed evenly in every role in the market. When reading the instruction, we emphasized the fact that they would be playing against computer agents instead of other subjects in the room. A trial run was conducted before formal experiments, and their opponents in the trial run were Zero-Intelligence traders with Constraint (ZI-C). The so-called ZI-C trader was proposed by Gode & Sunder (1993) and what it does basically is random bidding/asking in a range constrained by its token values. We used ZI-C traders in the trial run to provide our subjects enough training but not too much information about the computer traders they were going to encounter later.

The participation fee for the double auction experiment is NT$200, and the fee for the WMC test is NT$300. We also provided additional reward to subjects if they performed well in the auctions: a subject ranked No.1 in his/her own market would get an extra NT$250; a subject ranked No.2 in his/her own market would get an extra NT$150; a subject ranked No.3 in his/her own market would get an extra NT$75. Even if the subjects did not get the additional bonus, the participation fee itself is still higher than the average hourly wage rate of a part-time job in Taiwan and should therefore provided strong monetary incentives for the subjects to play seriously. Most of our subjects are undergraduates, and some of them are graduate students. The recruiting job was done through internet, and our subjects were from different departments in different universities.

3.5 Results and Analysis

Noting that in the market experiment human subjects' opponents in the market are non-adaptive and truth-telling agents. Our question is: *is there a positive relationship between social heterogeneity in terms of working memory capacity and economic inequality in market exchanges in a nearly static environment?*[9] Our hypothesis is that the larger a subject's working memory capacity, the better he/she performs in the markets. We will firstly compare subjects' WMC scores and market performance, and then examine whether there is other evidence supporting our hypothesis.

We recruited 173 subjects from twelve experimental sessions. During the experiments, we noticed that there are subjects who made mistakes when entering

[9] It is not entirely static because the following two facts: first, even if all computer agents are truth tellers, the timing of their bids and asks are still influenced by the human trader's decisions; second, the system will randomly decide who is the current buyer/seller if the human trader's bid/ask price is equal to some agents' bid/ask price.

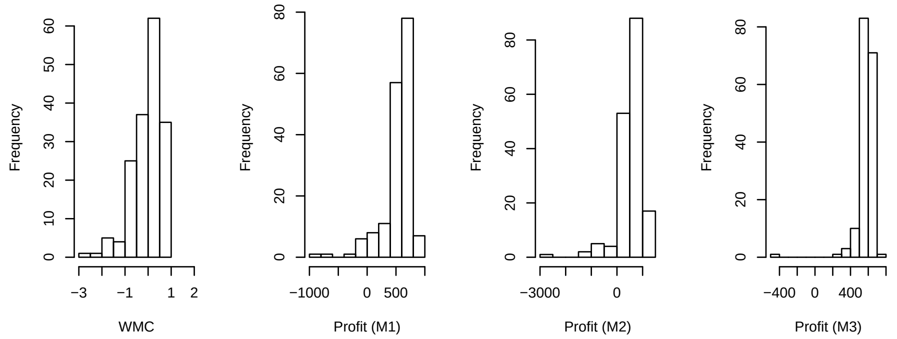

Fig. 6. The distribution of subjects' WMC scores and their performance

their decisions.[10] The most fatal mistake for buyers is to enter an additional digit while the most serious mistake for sellers is erroneously missing a digit. We also noticed that such mistakes would make their profit ridicously low and creating serious outlier effect. We therefore dropped the data from three subjects because their raw profit is ten times worse than the benchmark, that is, a subject is dropped if the performance index is below -1000 in a certain period.[11] As a result, the following analysis is based on a size of 170 effective subjects.

Can WMC Predict Subjects' Performance? To infer whether there is any relationship between WMC and subject's market performance, we first compare the distributions of these variables. Figure 6 demonstrates these distributions, and Table 2 gives the descriptive statistics. The distributions show that both the WMC and subjects' profits in each market are left-skewed, and the statistics confirm that the distributions are far from normal. The similarity of these distributions prompts us further to see what may connect these distributions.

To do so we first consider a simple regression model to access the effect of WMC on market performance:

$$E_i = \alpha + \beta\, WMC_i + \epsilon_i \tag{2}$$

where E_i refers to subject i's earning.

[10] In fact, subjects often raised their hands during the experiments because such mistakes would make them loss a lot.

[11] We choose this criterion because if a subject erroneously enter an additional digit or miss a digit, there is a ten-time difference and probably the profits will drop by ten-times. On the other hand, if we used normal statistical methods to identify outliers, we would have to drop the data from more than three subjects.

Table 2. Descritpive statistics

	WMC	Profit (M1)	Profit (M2)	Profit (M3)
Mean	−0.03	538.66	510.43	576.19
Median	0.11	600.5	557	591
Maximum	1	826	1157	723
Minimum	−2.66	−908	−2979	−500
Std. Dev.	0.64	262.61	470.11	105.13
Skewness	−1.09	−2.32	−3.34	−6.67
Kurtosis	1.58	7.44	18.51	62.87
Jarque-Bera	53.1125****	560.5756****	2814.377****	29978.27****

Significant at the 0.1% level: ****
Significant at the 1% level: ***
Significant at the 5% level: **
Significant at the 10% level: *

Table 3. Estimated coefficients of WMC scores on market performance from simple regressions

Variable	Profit (M1)	Profit (M2)	Profit (M3)
Constant	542.57***	515.64***	577.52***
	(19.10)	(35.10)	(7.77)
WMC	133.93***	178.43***	45.74***
	(29.68)	(54.55)	(12.08)
R^2	0.1081	0.05988	0.07868

Note: Standard errors are in parentheses.
Significant at the 1% level: ***

Table 3 reports the results of these simple regressions for each market, and Fig. 7 depicts the actual fit. From Table 3, one can see that the coefficients in all three equations are significantly positive showing that a higher WMC does contribute to the a higher earning capacity, although the low R^2s suggest either that the earning capacity is under the exposure of great uncertainty, or that WMC is not the only contributing factor. It is the later possibility motivating us to have a second visit to the earning equation.

A More Complete Picture of WMC Scores on Subjects' Performance While the results from simple regression seem to support our hypothesis, the low R^2 indicates that our study of the earning equation may be far from complete.[12] But what can be left out? The general literature on experimental economics may suggest some possible relevancy of gender and experience. Therefore, we add these two variables into the earning regression. For the latter, based on the questionnaire at the end of the experiments we differentiate participants' experience in on-line auction (Yahoo, ebay), financial investment (stock, futures, currencies) and other kinds of auctions (antiques, commodities).

[12] Referring to the middle panel of Fig. 7, it is apparent that the sample is divided into two groups–a higher group and a lower group. The division of the two groups appears to be independent of the WMC scores, and it makes the regression line look spurious.

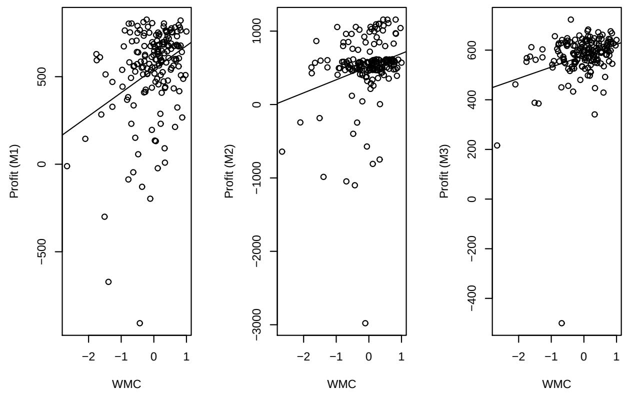

Fig. 7. Simple regressions

In addition to these four, we also consider the role of the subject in the market, i. e., either buyer or seller. This consideration is due to the fact that not all the three markets are symmetric, which in turn may be more favorable for one side of the market. Market 2 is particular the case (See Fig. 5, the middle panel) where, by the theocratical equilibrium, the producer surplus is overwhelmingly larger than the consumer surplus. This may cause sellers have an easy money to make then buyers. Therefore, to balance out this asymmetry, a role variable is also included.

Finally, very much motivated by Herbet Simon (Simon 1996), we have a variable on tool.[13] Hence, in sum, we have six additional variables to fed in the earning equation (now Equation 3), which provides information on gender, experiences, trading role, and tool dependence. The definition of these explaining variables are listed in Table 4.

$$\begin{aligned} E_i = \alpha &+ \beta_1 WMC_i + \beta_2 X_{1i} + \beta_3 X_{2i} \\ &+ \beta_4 X_{3i} + \beta_5 X_{4i} + \beta_6 X_{5i} + \beta_7 X_{6i} + \epsilon_i \end{aligned} \tag{3}$$

Table 5 reports the results of multiple regression. The first thing we notice is that *Buyer* seems to be a very important factor in determining subjects' performance. More specifically, being a buyer is advantageous in Market 1 but is disadvantageous in Market 2. To reason why being a buyer or not is crucial to

[13] In the questionnaire after the experiments, we ask whether they think the auctions difficult, and whether they would like to use paper and pencil to help decisions. Notice that subjects were not allowed to use any decision-support facilities during the auctions, this question simply wants to identify the subjects who were desperate for this kind of facilities.

Table 4. Explaining variables of the multiple regression model

Variable	Definition
X_1	An indicator variable equal to 1 if subject i is male.
X_2	An indicator variable equal to 1 if subject i is a buyer.
X_3	An indicator variable equal to 1 if subject i has experiences in online auction markets (such as eBay or Yahoo auctions, etc.).
X_4	An indicator variable equal to 1 if subject i has experiences in financial markets (stock, futures, or exchange markets).
X_5	An indicator variable equal to 1 if subject i has any other experiences in auctions (such auctions of antiques or agricultural products).
X_6	An indicator variable equal to 1 if subject i expressed the need of paper and pencil during the auctions.

Table 5. Estimated coefficients on market performance from multiple regressions

Variable	Profit (M1)	Profit (M2)	Profit (M3)
Constant	446.17****	546.1192****	593.62****
	(39.27)	(73.3441)	(16.63)
WMC	145.92****	159.3392***	43.72****
	(29.22)	(54.5807)	(12.38)
X_1	74.70**	151.5478**	7.64
	(37.67)	(70.3491)	(15.95)
X_2	107.25***	−229.4911***	−18.65
	(37.87)	(70.7335)	(16.04)
X_3	−47.95	−47.9077	−21.54
	(38.89)	(72.6339)	(16.47)
X_4	63.68	55.6353	−43.92*
	(53.56)	(100.0330)	(22.68)
X_5	28.27	0.4086	34.01
	(63.85)	(119.2451)	(27.04)
X_6	85.71**	128.6838*	21.43
	(39.95)	(74.6106)	(16.92)

Note: Standard errors are in parentheses.
Significant at the 0.1% level: ****
Significant at the 1% level: ***
Significant at the 5% level: **
Significant at the 10% level: *

profitability, we have to resort to the design of the market structure. From Fig. 5, we can see that while M3 is a symmetric market, M1 and M2 are asymmetric in the following aspects:

1. The theoretical equilibrium price is favorable for seller in M1 and M2.
2. Seller's sub-marginal tokens face stiffer competition if they want to steal deal from intra-marginal tokens.

Take M1 for example. The theoretical equilibrium price is a little more favorable for sellers, and we indeed find that sellers gained a little more profit than buyers for their first two (intra-marginal) tokens.[14] However, if a seller wants his/her first sub-marginal token to steal the transaction opportunity with a favorable

[14] Buyers' first tokens earned significantly less profits against sellers': an average 40.02 versus an average 42.26 raw profit. For the second token, buyers earned 15.22 and sellers earned 14.84, but the difference is not significant.

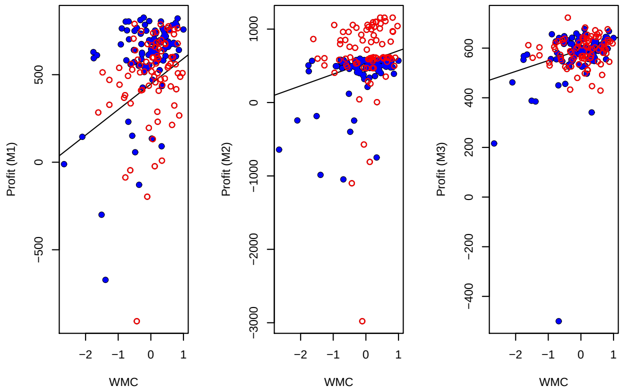

Fig. 8. Multiple regressions. Seller subjects are represented by red hollow circles, while buyer subjects are represented by blue solid circles.

intra-marginal buyer token, the ask price submitted has to be so low that this action usually turns out to be a disaster in terms of profit.[15] As a result, being a seller in M1 is disadvantageous because the little advantage in intra-marginal tokens was overwhelmed by the loss incurred from their sub-marginal tokens. In M2, the same asymmetries cause the same advantage in intra-marginal tokens as well as disadvantage in sub-marginal tokens for sellers. However, seller subjects in M2 *learned* to hold their impulse for sub-marginal tokens and refrain from getting loss. Therefore, sellers earned a lot more than buyers in M2. In M3, such asymmetries do not exist and therefore being a buyer or seller does not make any difference in terms of profit earned.

Controlling such an eminent factor on subjects' performance, we can see from Table 5 that WMC is still the most important factor in predicting subjects' profits in each market. The coefficients of WMC scores are still positive and not far away from the results in simple regression models. In sum, the WMC is the most significant and most contributive factor for profits earned no matter in which market structure in our experiments. Figure 8 illustrates this fact by separating buyers and sellers. Other factors, namely *Male* (gender) and *Tool*, do not have such pervasive influence as WMC has.

As can be seen from the beginning of this section, subjects' performance in three auctions are not normally distributed. The left skewed distributions suggest that while there are subjects who performed very badly, many subjects actually make lots of profit and are not so far away from each other. Although

[15] Our experimental data shows that in M1, buyers earned an average -3.2 against sellers' -10.64 raw profit for their first sub-marginal tokens. For the second sub-marginal tokens, buyers earned an average -23.62 and sellers earned -37.94 raw profit.

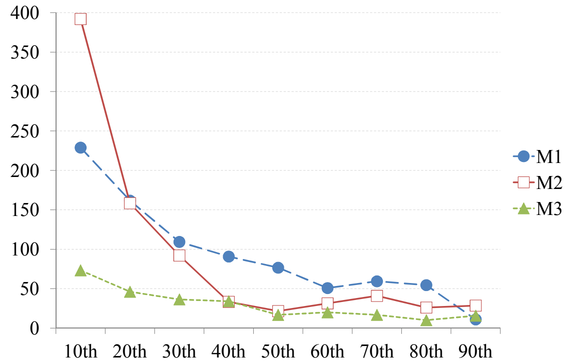

Fig. 9. Coefficients of WMC scores from quantile regressions for different percentiles–Exp 1.

the regression analysis indicates the significance of WMC, there is still suspect, based on visual inspection of Fig. 8, that such significance comes from few bad sample points which tilt the regression line towards the ones with positive slopes.

To be more precise, regressions based on ordinary least square only tell us whether WMC scores can predict the *conditional mean* of the performance, we don't really know whether such relationship exists everywhere in the distribution. Is WMC important for top players in the markets? Or WMC is important only for those who don't have the knowledge to well solve the decision problem in auctions? What is WMC's impact on profitability throughout the distribution?

To answer these questions, we use quantile regression to capture the relationship between WMC scores and performance for different percentiles of the performance. Table 6 reports the regression results for 10th to 90th percentiles. We have two observations:

1. WMC scores have significant prediction capability on profit for low, median, and high percentiles.
2. If we look at the magnitude of the coefficients more carefully, it seems that the higher the percentile, the smaller the coefficient.

The first observation suggests that the influence of WMC is not constrained to a specific group of subjects. But the second observation is very intriguing to some degree. Figure 9 visualize this finding by plotting the coefficients of the nine percentiles sequentially. It is obviously that, no matter what the market structure is, the coefficient drops drastically from low percentiles to higher ones.

The declining coefficients portray an interesting picture of the story: WMC scores are more important for those who perform worse, but its importance is less eminent for top players. One simple conjecture is that the profit a subject can earn is constrained by the number of intra-marginal tokens, the number of periods, the demand-supply schedules, and the behavior of other computer agents. In our experiment, computer agents are all truth tellers, so the demand-

Table 6. Estimated coefficients of WMC scores on market performance from quantile regressions

Percentile	Profit (M1)	Profit (M2)	Profit (M3)
10th	228.90173***	392.02586****	73.24561****
	(86.7869)	(97.39893)	(14.61504)
20th	161.71004***	158.4*	46.139***
	(58.82482)	(83.83734)	(15.67518)
30th	109.34066**	92.10526**	36.42857****
	(48.26477)	(43.0522)	(10.76415)
40th	90.78014***	33.33333	34.11765****
	(33.65762)	(25.45431)	(9.42353)
50th	76.60819***	21.57676	16.81818*
	(26.76408)	(19.23708)	(9.09175)
60th	50.79051*	31.38298**	20.0409*
	(26.41315)	(12.85336)	(10.48584)
70th	59.37500***	40.90909****	16.84533**
	(21.41526)	(7.0956)	(8.50958)
80th	54.54545***	26.1194*	10
	(19.31504)	(15.31615)	(6.17487)
90th	11.00917	28.59885***	15.71429***
	(22.5764)	(10.5902)	(5.9413)

Note: Standard errors are in parentheses.
Other factors used in multiple regressions are also used here as the explanatory variables.
Significant at the 0.1% level: ****
Significant at the 1% level: ***
Significant at the 5% level: **
Significant at the 10% level: *

supply schedules actually decide the highest profit a subject can earn in a single period.[16] With this limit, even if people with higher WMC *on average* can earn higher profits from market activities, the statistical relationship will be less manifest than it should really be for higher percentiles.

The Dynamics of Subjects' Performance We have seen that WMC score plays a significant role in predicting subject's performance, indicating that subjects with higher WMC perform better. The results of the quantile regressions further tell us that this effect is ubiquitous, albeit declining in magnitude. The importance of innate cognitive capacity leads to a scenario in which people with low WMC are predestined to earn less in markets, but is it really the end of the story? What if people can learn to improve? Will learning shrink or amplify the differences in people's market performance?

To answer the above questions, we have to examine WMC's contribution from a dynamic perspective: we want to know how WMC's influence persists over time. We divide the subjects into two groups–Group High and Group Low–according to their WMC scores. Subjects whose WMC scores is above zero are

[16] On the contrary, because we didn't impose budget constraints on traders, a subject (especially if he/she is a buyer) may incur huge loss if he/she makes a mistake. For example, if a buyer subject bids a very high price, the transaction price will be very high and therefore results in a huge loss. This asymmetry, we believe, may be able to explain why the distribution of profits earn is left-skewed.

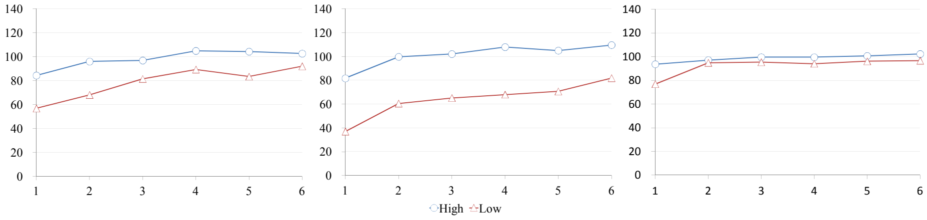

Fig. 10. The evolution of average performance for High and Low Groups–Exp 1. From the left to the right are average performance in M1, M2, and M3, respectively.

marked as High, others as Low. Figure 10 demonstrates the evolution of average performance of each group throughout the experiment.

From Fig. 10, we can easily observe several features: (1) It is obvious that the High Group outperformed the Low Group in every period of every market. (2) There is obvious learning for both High and Low Groups. (3) The gap between High and Low Groups shrinks overtime, suggesting that the advantage of having larger WMC is weaken when learning exists. (4) Subjects' performance drops when the demand-supply schedule changes. We will explore these visual features and judge whether they are reliable or not in what follows.

For the first observation, a quick look seems to indicate that subjects with above-average WMC tend to perform better than subjects with below-average WMC. To make sure that these differences are significant, we perform nonparametric tests on each period of these two experimental series. The null hypothesis assumes that the High Group and the Low Group have the same performances, while the alternative hypothesis states that the High Group has higher performances in average. Table 8 in Appendix C reports the results of the Wilcoxon rank sum tests. The null hypothesis is rejected in almost every period in every market, therefore it validates our first observation.[17]

Further inspection of Table 8 reveals that while the performance index of High Group surpasses 100 in all the markets, that of the Low Group fails to do so. Notice that we use performance index described in Equation 1. In this sense, 100 refers to the case that a subject do nothing but just bid/ask according to the assigned token values. The fact that High Group eventually can achieve an index higher than 100 indicates that subjects in this group managed to come up with better decisions than truthfully bidding/asking. On the other hand, the Low Group would like to try something different from the truth-teller strategy; however, a performance index below 100 indicate that these efforts are made with no avail. From the performance of these two groups, we might also be surprised by the fact that the seemingly naive truth-teller strategy is too formidable to beat. One of the possible reason is that when all market participants (artificial agents) become truth-tellers, the competition could be keener than we might think. Any

[17] The few exceptions are period 5 & 6 in M1 as well as period 1 & 2 in M3, at the 5% significance level.

greedy bid or ask may cause the loss of a profitable trading opportunity with the presence of these truth-telling competitors.

As the second finding, we first notice that the upward trend is graphically evident for both groups in all three markets. To get closer scrutiny, we define the *effect of learning* as the improvement made by the subject from period 1 to the last period and then conduct Wilcoxon Signed Rank Test to see whether it is greater than zero. The test results confirm that subjects did make significant improvement throughout the experiments (see Table 9 in Appendix C). Now, if both groups can learn and make improvements over time, then would they be able to learn in a different rate that eventually the Low group can catch up the High group? In other words, will the significance of cognitive capacity decrease over time and learning plays a dominate role as times goes on? This is pertaining to our third observation.

Figure 10 shows that the difference in the earning performance between the two groups shrinks throughout the experiments, but statistical tests in fact indicates no significance (Table 9, last column). Hence, we cannot conclude that the Low group is catching up the High group. The rejection of the convergence pattern comes from the high variation of the Low group. In fact, we find that the learning capability of the low-group subjects are much more heterogeneous than the learning capability of the high-group subjects.[18]

Even though there is no significant evidence to show that the gap get narrower, the gap seems to be different among different markets. From Fig. 10, it can be seen that it is widest for M2, and narrowest for M3. This ranking seems to be consistent with the ranking of the hardness of three market as we discussed in Section 3.4 where we argue that by our design strategy to earn may be the least sophisticated in M3 and the most sophisticated in M2. Therefore, the third fining of this experiment can be rephrased as follows: the earning performance of the Low group constantly falls behind that of the High group, and the size of the gap depends on the hardness of the decision problem implied the market topology. One may argue that learning along the sequence of the three market experiments can make the last market experiment be the easiest one and the first the most difficult one. It is exactly because of this concern we did put M1 before M2. Hence, one can say that even though the cross-market learning might be expected, its real effect can still crucially depend on the hardness of the problem.

Let us continue examining the cross-market learning or adaptation. For both groups of subjects, when a new market is presented, there is always a drop in earning performance. For the High group, it was dropped from 103 to 82 (when M1 was replaced by M2) and from 110 to 94 (when M2 is replaced by M3). The similar pattern of earning performance also holds for the Low group: 92 to 37 at the first transition, and 82 to 77 at the second transition. Among the two transitions, the first one is more challenging because it is a transition from a

[18] We also conduct regression analysis to examine whether subjects' WMC scores can predict their effects of learning. The results are far from significant for all three markets, indicating that WMC cannot explain the amount of improvement subjects had made.

relative simple decision problem to a more difficult one. It is then interesting to notice that the Low group suffers more than the High group during the adverse transition: a 60% drop for the Low group as opposed to a 20% drop for the High group. Therefore, our evidence supports that cognitive capacity matters not only for the within market learning, but more importantly for cross-marking learning and adaptations to new environment.

4 Concluding Remarks

The aim of this project is to study how human subjects deal with decisions under uncertainty, especially when the probability is not known in advance. We also want to know if subjects' behavior is heterogeneous, and what kind of personal factors influence their behavior.

We discuss the possibility that the heterogeneity in human's cognitive capacity has effects on their market activities. A lot of research in the past suggested that the heterogeneity in human's innate characteristics has something to do with economic inequality observed in our society, but few attempted to test this in a market context close to our daily market experiences.

Can cognitive capacity explain the differences in people's behavior? Our results show that WMC is an important factor in predicting subjects' performance in double auction market experiment. However, the only exception reminds us that WMC's influence may not be universal.

If cognitive capacity, measured as WMC, is really a decisive factor even when people can learn and gain experiences? Although we observe that learning does happen, we don't have evidence strong enough to indicate that it can eliminate the differences in performance resulting from the heterogeneity in innate capability.

The results of our analysis bring about an important issue regarding bounded rationality. Herbert Simon made it very clearly that cognitive limitations and the structure of the environment, like a pair of scissors, shape our bounded rationality (Simon, 1996): we have to look at them simultaneously. Likewise, one have to be very careful in interpreting our findings here since we have little knowledge about how subjects actually make their price and timing decisions. We need more detailed evidence to clarify the role of cognitive capacity in complex economic decision making. A further exploration into subjects' detailed bidding/asking behavior, maybe with the help of advanced neuroeconomic methods, could be helpful.

Appendix

A Subjects' Redemption Prices (Token Values) for Each Market

The following table presents the reservation prices of buyers and costs of sellers (the redemption values, or the token values) for our three markets. The values are decreasing for buyers, obeying the rule of decreasing marginal benefits of buyers. The values are increasing for sellers to imply increasing marginal costs.

Table 7. Subjects' Redemption Prices (Token Values) for Each Market

M1	Buyer 1	Buyer 2	Buyer 3	Buyer 4	Seller 1	Seller 2	Seller 3	Seller 4
Token 1	390	390	390	390	310	310	310	310
Token 2	370	370	370	370	340	340	340	340
Token 3	356	356	356	356	360	360	360	360
Token 4	338	338	338	338	372	372	372	372
M2	Buyer 1	Buyer 2	Buyer 3	Buyer 4	Seller 1	Seller 2	Seller 3	Seller 4
Token 1	164	160	156	152	30	34	38	42
Token 2	108	112	116	120	154	150	146	142
Token 3	104	100	96	92	158	162	166	170
Token 4	76	80	84	88	186	182	178	174
M3	Buyer 1	Buyer 2	Buyer 3	Buyer 4	Seller 1	Seller 2	Seller 3	Seller 4
Token 1	1300	1275	1250	1225	700	725	750	775
Token 2	1125	1150	1175	1200	875	850	825	800
Token 3	1100	1075	1050	1025	900	925	950	975
Token 4	925	950	975	1000	1075	1050	1025	1000

B The Information Revealed to Subjects

Figure 11 is a snapshot of what our subjects would see on their screens. Subjects enter their decisions on the left part of the window by entering their bid/ask prices. The button of "pass" means subjects can choose to pass this trading step without sending any price. There is a small table on the top of the window, which reports the token values for our human subjects in each market. Another small table in the bottom reports the raw profit earned in each trading period.

The main body of the screen consists of a large table containing all market information revealed during the experiments. The information disclosed are as follows:

- Column 1: The index of trading period
- Column 2: The index of trading step
- Column 3–6: Past bidding prices from buyers
- Column 7–10: Past asking prices from sellers
- Column 11: The winning buyer and its bid price ("- -" to indicate no buyer won because of a failure of reaching a transaction at the last step)

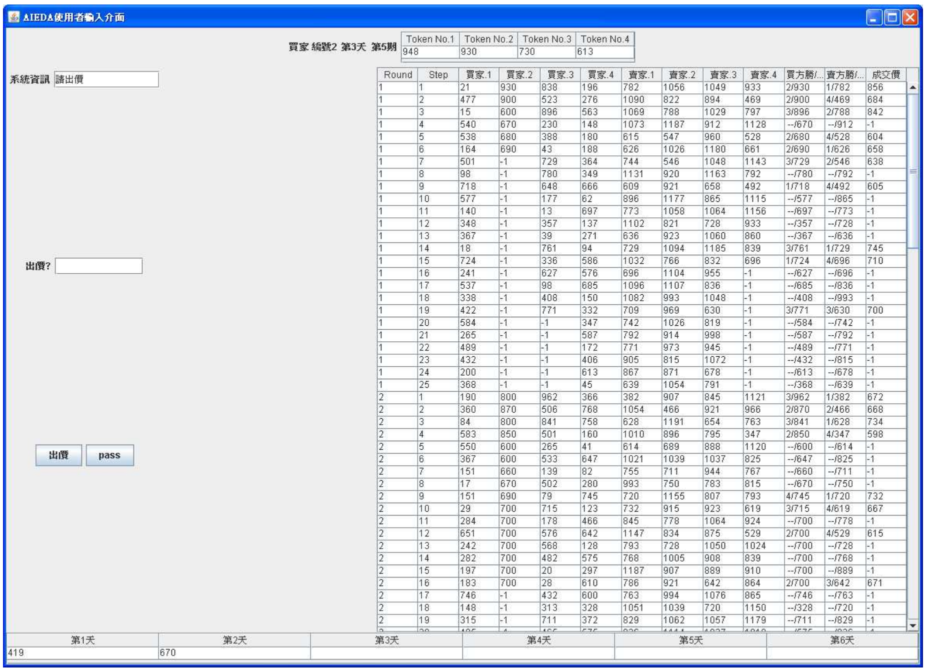

Fig. 11. A sample snapshot of the auction information presented to our subjects during experiments.

– Column 12: The winning seller and its ask price ("- -" to indicate no seller won because of a failure of reaching a transaction at the last step)
– Column 13: The transaction price. ("-1" to indicate no transaction took place at the last step)

C The High-Low Comparisons of Subjects' Performance in Double Auction Experiment

Table 8. Results of Wilcoxon rank sum tests for the High-Low comparisons–Exp 1.

	M1			M2			M3		
Period	High	Low	p-value	High	Low	p-value	High	Low	p-value
1	84 (39.93)	57 (97.47)	0.0434	82 (60.83)	37 (116.73)	0.0021	94 (19.85)	77 (122.14)	0.1328
2	96 (33.21)	68 (89.87)	0.0015	100 (53.82)	61 (92.83)	0.0004	97 (11.40)	95 (11.66)	0.1279
3	97 (41.91)	82 (66.50)	0.0386	102 (67.41)	65 (118.54)	0.0037	100 (8.47)	95 (12.18)	0.0113
4	105 (30.75)	89 (50.14)	0.0504	108 (56.08)	68 (123.24)	0.0048	100 (11.89)	94 (16.00)	0.0023
5	104 (37.29)	83 (76.24)	0.0945	105 (61.38)	71 (120.53)	0.0171	101 (11.24)	96 (12.86)	0.0017
6	103 (45.65)	92 (54.12)	0.2100	110 (57.15)	82 (93.46)	0.0065	102 (9.05)	97 (11.94)	0.0001

Note: Standard deviations are in parentheses.

Table 9. The effects of learning in the double auction experiment

	High			Low			High v.s. Low?
Market	Average	S.D.	p-value	Average	S.D.	p-value	p-value
M1	18.30	50.28	1.412E-07	35.25	82.41	6.860E-07	0.4005
M2	27.92	52.76	2.313E-10	44.86	79.99	1.838E-07	0.1712
M3	8.64	18.86	3.402E-10	19.77	121.55	0.00012	0.2677

The 2nd to 7th columns of Table 9 reports the average and standard deviation of the effect of learning as well as the p-values of the Wilcoxon Signed Rank Tests for whether the mean is different from zero. These statistics confirm the improvement made by our subjects.

The last column of Table 9 presents the p-values of Wilcoxon Rank Sum Tests on the effects of learning of both groups under 5% significance level. We therefore cannot conclude that the Low Group exhibits larger improvement although its average improvement is indeed larger.

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Report on the 2011 Economics Science Association International Conference

戴中擎
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參與會議過程

今年的 ESA 國際大會由芝加哥大學（University of Chicoga）以及普度大學（Purdue University）所主辦，芝加哥的 Kenneth and Anne Griffin Foundation 亦為主辦單位之一。大會由七月七日的 Pre-conference Panel 開始，到七月十日下午的 Informal Social Program 結束，歷時四天，地點則選在美國伊利諾州的芝加哥大學的 Booth School of Business。

雖然本屆大會地點選在芝加哥大學的 Booth Business School 而不是經濟學系，但芝大經濟系的 John List 教授卻是本屆大會的 Organizing Committee 之一。ESA 國際大會是由 ESA 所主辦，ESA（Economic Science Association）成立於 1986 年，其首屆主席為 Vernon Smith，亦即 2002 年諾貝爾經濟學獎之得主。ESA 成立的宗旨在於促進以實驗為主的經濟學研究方法，之所以在其名稱中特別強調"科學"的目的則是強調經濟學應是一門觀察的科學，並認為利用受控制的實驗（Controlled Experiments）來進行各種概念的探討是有其必要的。而特別之處在於 ESA 不但是一個經濟學的學會，也觀迎來自心理學、政治學、及其他相關領域的研究。

議程安排

本屆年會主要議程的部分共持續三天，分為八場 parallel session，每個 parallel session 時段有十個主題同時在十間演講廳進行，而每個 topic 中則有四篇論文報告。因此本屆大會共有約三百多篇論文報告。雖然論文眾多，但美中之不足之處則是由於同時間進行的 session 數量過多（每個時段內有十場報告同時進行），因此與會者必須在過多的論文間進行取捨，因此可能會錯過許多具有高度參考價值的報告。

除了論文報告外，大會亦邀請學者進行主題演講。本人參與了大會所安排的所有主題演講，其主題及講者資訊如下：

1. “Strategic communication”
   Tore Ellingsen, Stockholm School of Economics

2. “Prevalence, Determinants, and Consequences of Risk Attitudes“
   Armin Falk, University of Bonn

3. “The Role of Theory in Field Experiments: Evidence in Voting and Charitable Giving”
   Stefanol DellaVigna, University of California, Berkeley

大會議程中，本人所參與的議程以及聆聽的論文場次為：

Session 1

- Bargaining – 1: 「Focal Points in Unstructured Bargaining Situations」
- Incentives – 2: 「Whose Money is it Anyway? Using Prepaid Incentives in Experimental Economics to Create a Natural Environment」
- Markets – 3: 「Gift Exchange versus Monetary Exchange: Experimental Evidence」
- Contest – 4: 「Time Discounting in Strategic Contests」

Session 2

- Biology and Human Factors – 1, 2, 3, 4

Session 3

- Neuroeconomics – 1, 2, 3, 4

Session 4

- Generalizability of Lab and Field – 1, 2, 3, 4

Session 5

- Communication 2 – 1: 「An Experimental Implementation of Multimensional Cheap Talk」
- Social Preferences 1 – 2: 「Simple Tests of Social Preferences: Inequity Aversion and Efficiency Revisited」
- Communication 2 – 3: 「Distinguishing Honesty from Bounded Rationality in Cheap Talking Using Vagueness」
- Auctions 1 – 4: 「The Law of One Price in Auctions with Outside Competition」

Session 6

- Auctions 2 – 1: 「Sequential vs. Simultaneous All-Pay Auctions: An Experimental Study」
- Learning – 2: 「Cognitive Ability and Learning」
- Coordination 2 – 3: 「Economic Psychiatry: Abnormal Responses of Autistic Adults in Social Coordination Games and Socially-Influenced Charitable Giving」

Session 7

- Methodology – 1: 「A Validated Preference Module」
- Beliefs and Biases – 2: 「Visual Reminders Reduce Costly Hindsight Bias」
- Stability of Preferences – 3: 「Time Consistency: Stationary and Time Invariance」
- Law, Ethics, and Policy Implications – 4: 「Counterterrorism Strategies in the Lab」

Session 8

Health Economics – 1: 「Breast Feeding and Preference Formation」
Health Economics – 3: 「Are You What You Eat? Experimental Evidence on Risk and Time Preferences and Health Habits」
Sequential Decision-Making – 4: 「Predicting Behavior across Games – Can Personality Help?」

本人的論文「Human Factors in the El Farol Bar Experiment」則是發表在第一天下午的 Session 2。

與會心得

本人將對這次會議所有發表進行一個簡單的統計敘述，希望能呈現出一些顯著的趨勢。接著再針對相關議題進行探討。

首先，在會議過程中很明顯地可以感受到各大學系所在實驗經濟學研究能量上的差異。本人稍微統計了各大學的論文發表篇數如下：

10 篇以上	Caltech (California Institute of Technology) – 13 University of Heidelberg – 10
9 篇	Ohio State University
7 篇	Florida State University University of Michigan
6 篇	The University of Chicago Purdue University Peking University
5 篇	University of Pittsburgh University of Zurich
4 篇	University of Bonn

上表所列的內容，雖然不一定與其研究品質成正比，且各單位研究主題不儘相同，但多少可以反映各研究機構中從事真人實驗的多寡比例，也許可以作為國內對實驗方法有興趣的學生或年輕學者開始向外接觸的一個參考。

其次在議題分配上，若我們將議題區分為「市場實驗」和「賽局實驗」兩個類別來看，絕大部分的論文仍屬於賽局的研究。而本人這次與會主觀感受到最重要的兩個主題，則是「**個人偏好及個體因素之異質性**」以及「**田野實驗**」這兩個方面的研究。這兩方面的論文發表，不但在本次大會佔有一定的數量，而且大會本身就安排了兩場主題演講，本人將分述於後。

田野實驗

在受控制的實驗室中研究受測者的行為，一直都是實驗經濟學中的主流方法。Stefanol DellaVigna 在他的主題演講中利用實際的數字說明了這一點：由 1975 年至

今，在經濟學的五大期刊（*American Economic Review*, *Quarterly Journal of Economics*, *Journal of Political Economy*, *Review of Economic Studies*, *Econometrica*）中，Lab : Field 的研究論文數為 308:84。由數量來看雖然田野實驗的重要性似乎遠低於實驗室實驗，但若觀察這段期間內論文篇數的動態，則可知道兩者的研究論文在五大期刊中都呈現成長的態勢，也就是說田野實驗的研究也一直在成長之中。那麼，為什麼要強調田野實驗的重要性呢？DellaVigna 的看法是：相較於實驗室中的實驗，田野實驗的描述性是較高的（more descriptive）。這個觀點的另一面即是：就實驗結論推及真實世界的能力（Generalizability）而言，田野實驗是比實驗室實驗好的。

以本人對實驗文獻的瞭解，這樣的觀點至少有兩方面的支持理由：

1. 實驗室中難以重現真實決策中的各項條件和心理狀態
2. 在實驗室中難以去除掉觀察者或社會壓力的影響

就第一點而言，可以參照 Levitt and List (2007) 所列的理由，包含背景情境（Context）、利害大小（Stakes）、受測者自我篩選問題（Self-selection）、選項及時間的限制（Restrictions on Choice Sets and Time Horizons）等問題，都阻礙了實驗室實驗的可一般化能力（Generalizability）。

針對第二點，實驗室中雖可透過雙盲設計（double-blind approach）或隨機回應（randomized response）來增加匿名性（anonymity）。隨著匿名性的提高，希望能消除掉實驗者對受測者觀察的影響（Scrutiny）。在這個因素上最廣為人知的研究，莫過於 List (2006) 的球員卡交易實驗。這次的主講者之一 Stefanol DellaVigna 則是以他自的在公益損款及投票調查的田野實驗中，藉由面訪或傳單的方式進行調察，明確地展示了社會壓力（Social Pressure）對個人行為意向的影響。

綜合以上幾點，實驗室實驗的結果在推論到真實行為之前，似乎都應該要接受更嚴格的檢驗才對。然而就在短短二十分鐘的 coffee break 之後，剛聽完 DellaVigna 演講的諸多會眾轉移場地到了第四場 session，聆聽實驗經濟學泰斗 Colin Camerer 的發表，對 DellaVigna 和 List 的見解提出了犀利的挑戰。Camerer 的報告雖然只有短短二十分鐘，卻足夠他針對 List 等人強調田野實驗在推論真實行為的能力（generalizability）優於實驗室實驗的論點進行了言簡意駭的反駁。

在面對所有針對實驗室實驗推論能力的質疑時，Camerer 提出三項重點：

1. 大部分的因子都可以在實驗室內被控制
2. 實驗室實驗和田野實驗的結果差距並沒有想像中的大
3. 實驗可複製性（Replicability）是科學知識累積的基石

針對第一點，Camerer 舉例說明心理學家可以利用巧妙的設計（如謊稱理由來觀察受測者行為）來大幅地降低實驗者觀察對受測者的影響。針對第二點，Camerer 進行文獻的回顧，並以 List (2006) 的數據說明其實兩種實驗方法所得到的行為差異並不大。最後，Camerer 認為實驗室實驗較易複製，田野實驗反而干擾因素更多，更不易複製。而實驗可複製性則是科學研究過程中不可撼動的一項基本要求。再者，Camerer 也指出田野實驗過程中所作的假設並不少於實驗室實驗。總言之，Camerer 站在了替實驗室實驗

辯護的這一方，認為實驗室實驗的結果仍具有高度的參考價值。

在綜觀各方觀點後，本人認為雖然田野實驗的確較實驗室實驗更為貼近現實，但並不表示實驗室實驗便不具高參考價值。考量研究者的研究目的以及不同問題的領域，適合採行的方法理應不同。就以公益捐獻行為為例，批評者常論在實驗室中，因為有社會壓力的存在，致使受測者有相當高的捐獻比例。然而我們不能忘卻的是，在現實世界中的許多捐獻選擇就是在有社會壓力的情況下進行的─實驗室中的社會壓力不一定代表脫離現實。研究者應該具備更細心於區分研究特性，並挑選適當的實驗方法，而不是盲目地採行某種特定方法。

個人偏好及個體因素之異質性

決策個體的異質性，諸如人格特質、智力、性別等等，一直以來在經濟學中都沒有收到足夠的重視，有論者指出個體綜使具有異質性，但一方面不足以對其行為產生重要的影響，另一方面則是因為經濟理論著重於一般性，所以個體差異可忽略。那麼到底實情如何呢？個體的異質性對行為的影響可以在哪些層面觀察到？其對個體偏好的影響又是如何呢？

在本屆大會中，除了有至少四篇論文探討這個議題外，在第二場主題演講中，Armin Falk 更是簡明地呈現了各項個體因素對人類偏好的影響。Armin Falk 問的問題很簡單：眾所週知人類的行為會受到其偏好（諸如風險態度、時間偏好等）的左右，而個體之間的偏好也存在相當大的差異，那麼這些差異可以利用個體之間的異質性來解釋嗎？Armin Falk 本人的研究及其所搜集的文獻顯示出令人驚訝的結果：就風險偏好及時間偏好而言，智力、性別、人格、甚至年齡和身高體重對人們的偏好都有統計上相當顯著的影響！例如：男性較女性較能承受風險；年齡愈大風險承受能力愈低；身高愈高者風險承受能力愈高；智商愈高者愈能承受風險等。Armin Falk 甚至透過對家針單位的資料研究得知子女的風險及時間偏好會不偏不倚地全數遺傳自父母。男孩的偏好較多來自於父親，而女孩的偏好則較常承襲自母親。

或有論者認為就經濟建模的角度出發，個體之間偏好若存在差異，那麼直接衡量其偏好間的差異即可，何需大費周章納入更多其他因素呢？對此，Falk 提出一個簡單的問題：人格特質和偏好在解釋人類行為時是替代的（substitutes）還是互補的（compliments）關係？

Armin Falk 的研究顯示出個體異質性對偏好的影響並非全面的，而是domain-specific 的。舉例而言，前述諸多因子對時間偏好及風險偏好的影響，在社會偏好（social preference，Falk 在此指的是 trust behavior）則沒有影響。簡言之，本人認為如果個體間的偏好差異可以完全和他們的其他特質上差異有穩定且普遍的聯結（替代關係），那麼除非是知識上對於偏好形成原因的追求，在建模時其實可以直接衡量偏好而不必訴諸其他因素。但如果偏好和其他個體因素間在不同問題上的解釋方向不同（互補關係），那麼在建模時同時考量偏好以外的因素便是必要的了。但不論如何，畢竟經濟學家對偏好形成的過程所知極度有限，在建模時不假設偏好是唯一或最重要的解釋因素是相當合理的。

與本人研究相關之心得與收穫

這次與會最直接的收穫便是在論文發表後所收到的建議。首先是 Colin Camerer 表示本人的實驗可以下調樣本大小，以更多的樣本數來提升結果的有效性。這個問題其實是很重要且有趣的，因為本人這次報告了兩場實驗的結果：實驗一有受測者 35 位，實驗二有 65 位。若按照 Camerer 的建議縮小樣本大小，假設每 10 人便成一組 El Farol 實驗，那麼 100 位受測就可以得到 10 組樣本。在同樣的成本下得到更多的樣本當然是件好事，但樣本大小還有更深遠的影響。

El Farol 問題是少數賽局中的一特例，我們可以想像參與的人愈多，或許整體達成均衡的可能性就愈低（因為協調較為不易，且在人數眾多的情況下施行懲罰性行動的效果較差）。在 El Farol 賽中存在著兩種互動的可能：其一是競爭的強若，其二是利用懲罰性行為來達成目的。這兩種可能性都與人數的多寡有關：首先，當人數眾多時，協調不易，若離門檻還有一兩個空位，受測者彼此之間的競爭性會比人數少時為大。再者，人數少時，或許可以透過懲罰性的行動（如採用玉石俱焚的出席行為來迫使他人採行某種行為以達成某種分配的目的）來影響他人的行為。因此，人數多寡確實是影響受測者行為的一個重要變數。

再詳細點說，當人數低於門檻時，已出席者因為已獲得好處，所以在下一期應繼續出席。[1]相反地，未出席者在下一期可選擇出席以獲取潛在報酬。因此，在人數低於門檻時，若受測者人數愈多，則潛在出席者人數就愈多，因此每個潛在出席者所面對的競爭人數就愈多。在這種狀況下，不同人格特質的受測者可能就會對競爭壓力採取不同的策略。

在另一情境下，當出席人數已經過多時，若有某些人寧可犧牲利益而堅持不退，則有可能迫使其他人退出，使留下來的人獲得好處。這樣的作法在人數少時較具針對性，因此理論上較容易成功；在人數非常多時，很難想像一個人的決策會對其他眾多的人產生喝阻。

若以上兩點臆測有可能發生，則人數多寡就會影響受測者的行為。而我們也唯有實際地測試不同人數的實驗才能得到回答。

意見交流及學術網路

這次不僅是本人所報告的論文獲得回饋，同時也發現其他的學者所進行的實驗與國內研究者的實驗不謀而合。例如，Armin Falk 的研究便與政治大學陳樹衡教授的國科會研究計畫相關。

[1]這是在假設已出席者為 level-1（本次大會可見 level-k 模型的使用似乎愈發廣泛）所得到的推論，在假設他人行為為隨機情況下，選擇出席是最好策略。利用 level-k 模型來思考 El Farol 問題有個優點，是我們可以將受測者的策略和其個人特質（如智商或人格等）作連結。

最特別的，莫過於 Cornell University 的 Victoria Prowse 與其同儕利用瑞文氏智力測驗來探討受測者在 Beauty Contest 中的預測行為。其研究方法與政大經濟系杜業榮博士候選人所進行的實驗如出一轍。本人有幸與 Prowse 討論，並於會後利用 email 引介杜同學與 Prowse 認識，希望能激起一些更有趣的學術討論火花。

建議

在實驗方法於經濟學中日益重要的今日，本人藉由此次與會再次驗證心理學在經濟研究中的重要性，會場中處處可見心理學研究的影子。因此建議國科會對於結合經濟學與心理學的研究應多予鼓勵。

攜回資料名稱及內容

1. 會議議程及論文摘要手冊一份
2. 會議摘要集及與會成員通訊錄一份

相關文獻

List, J.A. (2006). The behavioralist meets the market: Measuring social preferences and reputation effects in actual transactions, *Journal of Political Economy* 114(1), pp. 1-37.

Levitt, S.D., and List, J.A. (2007). What do laboratory experiments measuring social preferences reveal about the real world? *Journal of Economic Perspectives* 21(2), pp. 153–174.

Report on
The 2011 Annual Meeting of the Academy of Behavioral Finance & Economics

September 21-23, 2011, UCLA, Los Angeles, CA, U.S.A.

戴中擎

東海大學經濟學系

參與會議過程

由於今年的 ABF 年會舉行日期在本校開學之後，故能夠出國的時間相當有限。本人抵達加州大學洛杉磯分校（UCLA）時已是會議前一天深夜，並且於會議結束後隔天立即返國。所幸此次大會第一天的活動從下午開始，所以可以全程參與，而沒有任何疏漏。

Annual Meeting of the Academy of Behavioral Finance & Economics 並非一定有悠久歷史的會議，就算以行為經濟或行為財務這兩個領域出現的時間點來看，這也是一個非常年輕的會議：今年的大會僅是第三屆而已。

雖然如此，今年的年會仍有相當多人參加（超過一百篇論文），而且根據本人與一些與會者互動後所收集到的反映得知，這個會議已是行為財務與經濟領域質量相當高的會議了。而此次會議更是邀請到諾貝爾經濟學獎得主 Vernon Smith 作為大會的 Keynote Speaker，使得此次大會成為一次質與量並俱的難得學術盛會。

這個會議由行為財務與經濟學學院「Academy of Behavioral Finance & Economics」所主辦，而由 UCLA Anderson School of Management 協辦，故此次會議便在 UCLA 的 Anderson School of Management 辦行。該學會也即將要發行期刊「Advances in Behavioral Finance & Economics: The Journal of the Academy of Behavioral Finance & Economics」，希望透過專屬的期刊來凝聚行為經濟乃財務領域的論文。

議程安排

本屆大會並有三天的議程。第一天為報到及解說，主要目的在介紹學會的網路社群。該學會利用現在最熱門的人際網路工具—社群網站作為學會重要的溝通工具。

第二天開始進入論文報告的議程，詳細的議程請見附件。本人所聆聽或參與的議程為：

9/22

9:00-10:15 **The Financial Crisis, Risk-Taking, and Active Investing**

10:30-12:00 Track A: **Trust, Financial Collapse, and the Finance Sector**

13:45-15:15 Track D: **Emotions, Risk Attitude, Asset Prices- I**

15:45-16:00 Keynote: **Adam Smith on Propriety and Human Behavior**, Vernon Smith

9/23

8:45-10:15 Track A: **Theory-II**

10:30-12:00 Track A: **Trust, Culture, and Leadership**

12:00-13:30 Track A: **Brain and Bubbles: New Research Findings and their Implications for Financial Decision Making Across Financial Markets**

13:45-15:15 Track C: **Decisions**

15:30-17:00 Track A: **Personality**

與會心得

本人此次與會的心得可以分為以下幾個方面分別陳述。

與會者與論文觀察

首先，就此次與會成員的觀察而言，雖然會議名為行為財務與經濟年會，但與會者卻大多都是財務背景，甚至有業界人士進行報告。例如，最後一天中午腦神經財務的報告人之一 Richard Peterson，他在拿到醫學博士後，先在 Stanford 大學擔任腦神經經濟學博士後研究員，現在則一方面在 Claremont Graduate University 擔任訪問學者，一方面則是一家資本管理公司的管理階層。像 Peterson 這樣跨業界學學界的報告者本人就至少聽了三場的報告。除了財務領域的與會者外，本人也見到管理學領域的論文也在這次會議發表。

其次，心理學者是這次大會主要的與會者來源之一。如同本人今年七月參加的 iESA 會議一樣，心理學者的加入使得經濟領域出身的研究者得已對人類經濟決策行為有更深一層的認識。而在可預見的未來發展趨勢裡，我們應該會見到心理學的研究方法和工具在行為經濟與財務研究中更全面的影響力。

研究趨勢觀察

研究方法趨勢

馬禮蘭大學（University of Maryland）的 James Howard 同時也是 Federal Reserve Board 的成員，在其演講中歸納了財務理論自上世紀以來研究典範的移轉（The Past, Present, and Future of Behavioral Finance），由下列的第一項移轉至最後：

1. Rules of thumb: 經驗法則
2. Rational being: 理性決策模型
3. Cognitive psychology: 與認知心理學的結合
4. Neuroscience: 與腦神經科學的結合
5. Unconscious factors: 無意識過程在決策上的影響

對許多研究者而言，腦神經經濟（或財務）通常已被當作是行為經濟與財務研究的前緣了，然而正如基因經濟學（genoeconomics）試圖更深入地挖掘影響人類經濟決

策的因子[1]，無意識過程也成為行為財務分析的非常前緣[2]。Howard 舉 David Eagleman 所著的科普《Incognito:The Secret Lives of the Brain》作為他見解的說明：由於人腦大多數活動都是無意識的，因此無意識的因子（unconscious components）對人類行為的影響可能遠比人類有意識的部分還來得大。

本人雖然對無意識因子對人們經濟與財務決策的影響抱持懷疑的態度，因為即使人類的「行為」大部分受無意識因子的影響，但人們在「決策」時受無意識因子影響的程度仍是有待研究的。然而不可否認的，似乎有愈來愈多的研究指出無意識因子的重要性。例如在本次大會中，Pace University 的 Colleen Kirk 的報名便是 “The Effect of Nonconscious Goals on Investor Choice”；而更有趣的研究則是紐約大學理工學院（NYU Polytechnic Institute）的 Philip Maymin 將美國歷年音樂告示牌（Billboard）前百大單曲的節拍變異（beat variance）與股價指數波動（Volatility）作相關分析，發現兩者具高度相關性。Maymin 的研究乍看之下似乎讓人覺得過份牽強，因為即使統計上呈現高度相關，又該如何去解讀兩者之間的關聯性呢？Maymin 提出的理論是因為 beat variance 高的音樂容易佔據人們大腦思緒，反之 beat variance 低的音樂在聆聽時則毋需使用太多腦資源。Maymin 的研究則是另一項無意義因子影響人類行為的例子。

各種決策因子之研究對理論及實務的衝擊

行為經濟學或行為財務學的發展會以何種方法影響人類的生活呢？行為經濟學常遭受質疑的一點就是其不過是一群在特定條件下發生特定行為反應的個案集合，只能解釋決策行為，而無法對人類一般性的選擇行為提出有系統的模型。如果沒有一個一般性的選擇模型，那麼經濟理論該如何提出政策建議呢？

經濟學研究者至今尚未充分掌握諸如情緒、信任、無意識因子等影響人類行為的機制與過程，也許當前還不能像我們對偏好的處理一樣提出足夠一般化的操作方法。但值得我們思考的是，是否一定需要一個像物理定律一樣”一般化”的系統，才能對人類的福址作出貢獻？經濟理論對人類福祉的貢獻一定得來自於大規模的政策或制度設計（例如對價格、稅率、數量的操弄），還是可以用其他更細緻的方式（如 Thaler & Sunstein 在《Nudge》一書中所揭示的方法）來達成？

本屆會議許多的訊息都讓本人逐漸感知到科學知識對社會的影響不一定要透過（對價格、數量的）政策操作來實現，尤其是在個體存在極大異質性時。Richard Peterson 以其在業界的經驗提出了許多成功運用（腦神經）財務知識來影響投資人作出正確決策的例子。例如在投資人委託投資公司時，先與客戶講定在各種狀況下的投資規則，當投資人因為市場泡沫而變得利慾薰心時，因腦神經運作原理，顧客的風險意識已受到壓抑，所以顧客已經無法理性作出決策了，此時便可利用最早便與顧客講定的投資規則來規範高風險的行為。

Peterson 舉的許多例子都顯示出行為經濟的知識確實能非常有效地幫助人們解決

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[1] 請參見 Benjamin et al. (2007) 。

[2] 例如 Cheng (2010)。

現實的問題。誠如 Thaler & Sunstein 所舉的許多例子相同，都是在特定情境下運用我們對人類行為的特定知識來督促人們作出更理性的決定。也許經濟學家是該開始思考一個問題了：經濟理論的舞台到底在哪裡？即使我們要處理的是像金融市場沫泡或恐慌這樣的大問題，是不是都得等到發生之後才以總體政策來抑制或補救（如救市措施），還是可以在一般的時候便運用行為經濟學的知識在各個小地方影響投資人作出較理性的決策？

人格特質與信任之重要性

在本屆大會中有相當多的文章探討人格特質對財務決策的影響，本人所見到除了一般研究者常用的 Big Five 之外，尚有 International Personality Item Pool（http://ipip.ori.org/）。

此外，信任（Trust）一般被認為會在賽局中扮演重要的角色，但在參加本次大會之後本人才知道個體與團體問的"信任"也是另一個相當重要的問題。大會中有至少四篇論文以個人與金融機構間的信任作為影響金融風暴影響的研究。本人雖然知識有學者探討各國國民信任感與經濟發展的論文，但一直無法理解其中關聯性。直到聆聽本次大會第一天的 Track A 議程後，才恍然大悟其中緣由。

簡言之，個體與金融機構間若缺乏信任（在金融風暴後尤其如此），至少會有以下兩種結果：個人不願意將金錢存到金融機構，導致貨幣供給減少，流動性不足；金融機構不信任企業，導致「雨天收傘」行為，致使企業經營調度狀況雪上加霜。主流的經濟理論中常以流動性陷阱來解釋貨幣政策在金融風暴後失效的情況，也許個體與金融組織間個「信任」亦可以作為另一個相輔助的概念來解讀風暴後的金融市場。

論文發表收穫

本人此次報告的論文題為「Heterogeneity in Boundedly Rational Traders? Results from Double Auction Experiments」，目的在於探討個體認知能力的差異對其在雙方減價市場中獲利能力的影響。

本人在報告後，接受到以下諸位學者非常具體的建議：

- 阿拉斯加大學（University of Alaska）的 Jonathan Alevy 建議本人在分析中加入各期的分析，以動態的方式來解讀工作記憶對獲利能力的影響。
- UCLA Anderson School of Business 的 Liu Yang 建議本人可參考其同儕 Mark Grinblatt 所作的一系列研究，特別是探討 IQ 與投資人投資組合的文章[3]。
- Liu Yang 亦建議本人參讀 University of Miami 的 Alok Kumar 系列研究。

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[3] 例如 Grinblatt, Kelohharju, and Linnainmaa (forthcoming)。

總感想

與會期間，本人入住於 UCLA 的學人旅舍（UCLA Guest House）。於是在美國的五天都在 UCLA 的校園中度過，於是有充足的時間造訪該校的各個角落。本人除了對該校校區之廣大與系所建築物之多（反映該校領域之全面性）感到印象深刻外，更被該校校園整體及眾多師生所反映出來的學術研究與學習氣習所打動。

本人也觀察到一個看似平凡但卻有重要意義的細節：在遍訪 UCLA 校園時，本人發現該校與腦神經科學（Neurosciences）有關的大樓至少有四棟之多，其中包含了專屬於腦神經科學與人類行為的建物。而根據此次一同與會的本人博士論文指導教授指出，這些位於南校區的建物都是二十年前沒有的（本人指導教授是 UCLA 博士）。這代表在過去十幾年間，UCLA 為了腦神經科學研究與教學的需求，至少興建了四棟大樓以供使用。這反映出腦神經科學在近十幾年來在科學研究上的急速發展。而從該校的硬體資源分配就得以明白，為何我國的國科會會在這兩三年斥資一億元以上的經費來推廣腦神經科學中的一個子領域─功能性核磁共振造影（fMRI）─與人文社會科學領域結合的研究了！而在經濟領域，這樣的研究便是行為經濟學研究的最前緣─腦神經經濟學，而這也正是此次大會最後一天中午的一整個議程的主題。

此次共同與會的政大經濟一位博士候選人（目前交換到 Caltech 進行研究）指出，同樣位於加州的 Caltech 光是 MRI 的機器就有三台之多，而國科會補助供人文社會領域研究所用的 MRI 至今尚在籌建階段。若我們不比經費多寡，光以認識到其重要性，到實際行動的時程看來，我們已經落後至少十年了。

縱觀以上數點，本人對國內經濟科學的研究進展著實深感焦慮：行為與實驗經濟學在國內的發展程度與國外相比起來相差多久？當國外原文教科書已經該領域納入經濟學原理教材的同時（如 Parkin 的教科書就已將 Neuroeconomics 列入書中），國內大多數經濟學者卻可能對該領域連聽都沒聽過。這樣的差距不能僅仰賴每年回國的少數年輕學者來帶動，畢竟不是每位歸國博士都從事這個領域。不論是在教學還是研究上，國內學者對於新研究方法與思維的態度恐怕需要更為開放才行。

建議

此次會議本人乃利用國科會計畫核定出國開會費用之剩餘款項出國，故在出國前需要先申請經費使用變更。建議未來在國科會計畫申請書中，所增列第二個會議作為候補，一旦因故無法參加第一個會議，或者第一個會議經費有利餘時，可以逕行參與第二個會議，而毋需再行變更，以節省研究人員與各校行政人員之時間與人力。

攜回資料名稱及內容

1.	會議議程一份

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Report on the Eastern Economic Association 2012 Meetings

戴中擎

東海大學經濟學系

參與會議過程

本屆的 EEA 年會在美國東岸的 Boston 舉辦，時間則為 3 月 9 日至 11 日。本人於 8 日夜間抵達，而於第一天（9 日）下午進行論文報告。本人與共同作者的另一篇論文則被排定在第二天（10 日）上午進行，由本人的共同任者同時也是博士論文指導教授陳樹衡教授發表，同時本人也在該場擔任另一篇論文的評論者。

此次是本人第一次參加 EEA 年會，也是第一次參加一個真正綜合性、不限特定方法或議題的經濟年會。因此這次大會對本人而言是一次珍貴的經驗，本人在此次大會中也把握了機會，聆聽了許多非本人領域（不論是方法上或是議題上）的論文發表。例如，本人此次參與了大會針對經濟學教育及教學的議程，也聆聽了有關「佔領華爾街」運動的報告。雖然聆聽這些議題不見得對自己的研究有立即而顯著的幫助或影響，卻是一個難能可貴的收穫，畢竟誰能準確地知道自己可以將所學在何時應用的適合的地方呢？

承蒙國科會同意本人所提之經費變更，參加此次大會對本人而言，不但在自己的研究議題上收到了建議與指教，也在更廣的層面上擴張了對經濟學的興趣和熱情。

議程安排

本屆 EEA 年會參加人數相當多，議題也十分多元。自 3 月 9 日早上開始至 3 月 11 日中午，同一時段均有非常多的場次同步進行。本人對於 EEA 2012 議程的想法歸結如後。

首先，本人認為在同一時段內安排了太多的議程，導致許多議程的參與者基本上就是該場論文的報告者，再加上非常少數的聽眾。本人認為這樣的安排雖然

可能使得參與者彼此有較緊密的互動空間，但實際觀察的的結果卻是討論不若其他會議般熱烈。試想一個 session 只有五到七人參加，其中三到四人為報告者，剩下的人可能還包含 session chair，在 session 分散而每場聽眾人數相當少的狀況下，自然討論情況便不如預期。而大會僅持續二天半，其實可以將大會延長為三個整天，降低同時段的議程數目，應會有比較多的討論。

其次，本次大會最後一天（3 月 11 日）適逢夏令時間之始，所有議程均"提早"了一小時，本人由於不諳此制度，因此到會場時許多議程早已結束，而錯失了學習的大好機會。此次大會其實有不少美國以外的參加者，但大會在議程上並沒有適當的提醒，對於錯過時間的人來說其實相當可惜。

與會心得

此次本人聆聽了許多與本人領域相異的論文發表，針對這些論文，本人視為一次學習之旅。以下本人僅就自己的研究議題，以及本人擔任 discussant 所評論的論文進行討論。

認知能力與喊價市場表現

本人此次報告的主題為交易者的認知能力與其在雙方喊價市場中的表現及行為特性。在報告後所接收到的主要建議和指教有如下：

Temple University 的 Charlotte Phelps 教授指出，本研究的結果十分顯著，應立投稿，她並建議可以將分析結果拆為兩部份，這部分的建議將在本人回國後立即完成。此外，在本研究中受測者的行為可分兩類：被動型喊價及積極型喊價，由於 Phelps 教授的研究主題包含了個體人格特質對經濟行為的影響，因此她也建議我們納入人格特質來解讀喊價行為類型的差異。

另一位不具名的與會者則提出另一個可能性：真正影響交易者採取被動或主動型策略的因素，可能是其主觀上認為自己的智能較其他人高或低的結果。這位與會者的建議其實有其潛在的重要性，因為在雙方喊價市場中難免需要對競爭對手的策略進行猜略，而在決策時考量自己相對於對方的智能其實是有意義的。例如在 level-k 模型中，個體往往（正確地或錯誤地）認為自己可以較他人多思考一個層次，但是有沒有可能個體在某些狀況下覺得對手的策略遠較自己來得複雜，因而退而求其次採取一些安全或保守的策略呢？本人回國後亦已經開始慢慢思考這個因素的可能性。

論文評論

本人在此次會談中負責評論來自 Stevens Institute of Technology 的 Germán Creamer 教授「Simulating Investors' Views in the Black Litterman Portfolio Optimization Model」一文。該研究結合了計算智慧方法、社會網路、以及財務理論上的 Black Litterman model，以 data mining 的技術淬取出與個股有關的質性資料，藉以掌握董事成員與財務分析師預測兩方面的影響，並進一步利用此資料來預測資產價格。Creamer 教授在這個議題上其實有一系列的文章，其見解相當具有原創性及政策可行性。本人認為這篇論文具有高度實用的價格，而本人對其的意見則可見本報告所附的投影片摘要。

建議

此次參加大會，本人去程及回程均花費了相當多的時間在轉機上。而且會議適逢開學期間，其實補課相當不易。再加上本人此次乃是申請經費變更才得到旅費補助，因此更是深深感到參與國際會議，特別是亞洲學者參加重要國議會議的困難與壓力。相較起來，歐美經濟學研究者同樣參加高品質的會議，地點往往就在歐美大陸，不論在時間與費用上均節省許多，而這些優勢都是亞洲研究者所沒有的。若是有一些重要年會能在亞洲舉辦，國內學者參與國際會議的限制便不會那麼嚴重了。因此依本人拙見，促成一些重要國際會議在我國舉行是否為政府一個值得大力推廣與協助的方向？倘若國內有學者（不論是否為經濟學領域）願擔此大任在台籌辦國際會議，政府應該要盡全力協助，長久下來應對提升國內研究的品質及國際能見度應會有非常大的助益。

攜回資料名稱及內容

- 大會議程一本

Using link mining for investment decisions: extending the Black Litterman model

German Creamer

The Problem

- There are some problems with Modern Portfolio Theory (MPT):
  - High input-sensitivity
  - highly concentrated portfolios
- Black-Litterman model

The Question

- What are the investors’ expectations?
- **CorpInterlock**:
  Corporate interlock + economic variables ---------------> forecast
  LogitBoost
- Uses the return forecast of the algorithm to substitute the investors' view of the B-L model

Results

- Simulations show that by incorporating the forecasts of the CorpInterlock algorithm, the B-L model can come up with portfolios with higher accumulated returns than porfolios generated with other inputs (equally weighted & market capalization)

Suggestions and Questions

- Can we gain any insight from the results?
  - Basic corporate interlock:
    advantage → power (cartels, coordinated actions)
  - Extended corporate interlock:
    the "earnings game“ → disadvantage on company's returns (distorts decisions)

Suggestions and Questions

- The "small world" property of a network may explain how information is transmitted, and can provide precious information for Agent-Based financial modeling.

國科會補助計畫衍生研發成果推廣資料表

日期:2012/12/27

國科會補助計畫	計畫名稱: 不確定情況下重複決策問題之實驗研究
	計畫主持人: 戴中擎
	計畫編號: 100-2410-H-029-001- 學門領域: 個體經濟學

無研發成果推廣資料

100 年度專題研究計畫研究成果彙整表

計畫主持人：戴中擎	計畫編號：100-2410-H-029-001-
計畫名稱：不確定情況下重複決策問題之實驗研究	

成果項目			量化：實際已達成數（被接受或已發表）	量化：預期總達成數(含實際已達成數)	量化：本計畫實際貢獻百分比	單位	備註（質化說明：如數個計畫共同成果、成果列為該期刊之封面故事...等）
國內	論文著作	期刊論文	0	0	100%	篇	利用本計畫所支持之研究已在國內會議發表以下兩篇論文： 黃虹瑋，戴中擎（2011），有限理性與決策行為:二元預測問題的實驗研究，東海大學第三屆財經商管研討會。 徐正杰，戴中擎（2012），個體認知能力與市場供需結構對價格發現過程之影響，東海大學第四屆財經商管研討會暨企業倫理實務論壇。
		研究報告/技術報告	0	0	100%		
		研討會論文	2	2	100%		
		專書	0	0	100%		
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（本國籍）	碩士生	2	2	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		
國外	論文著作	期刊論文	0	2	100%	篇	本研究有一論文已撰寫完成，篇名為「From Social Heterogeneity to Economic Inequality in Markets」，將投稿至 Journal of Economic Behavior and Organization。另有一篇 working paper 正在撰寫中。
		研究報告/技術報告	0	0	100%		利用本計畫研究而發表的研討會論文計以下四篇： Chen, S.-H., Tai, C.-C., Yang, L.-X. (2012), ’’’’ Heterogeneity in Boundedly Rational Traders?

							Experiments,'''' The 38th Eastern Economic Association Annual Conference (EEA 2012), Boston, MA, U.S.A., March 9-11, 2012. Chen, S.-H., Tung, C.-Y., Tai, C.-C., Chie, B.-T., Chou, T.-C. (2012),'''' Predicting the Prediction Market: Would Smart Agents Help?'''' The 38th Eastern Economic Association Annual Conference (EEA 2012), Boston, MA, U.S.A., March 9-11, 2012. Chen, S.-H., Tai, C.-C., Yang, L.-X. (2011), 'Heterogeneity in Boundedly Rational Traders? Results from Double Auction Experiments,' The 2011 Annual Meeting of the Academy of Behavioral Finance & Economics (ABF 2011), Univesity of California, Los Angeles, September 21-23, 2011, Los Angeles, California, U.S.A. Tai, C.-C., Gostoli, U., Chen, S.-H. (2011), 'Human Factors in the El Farol Bar Experiment,' The 2011 Annual International Meeting of the Economic Science Association (ESA 2011), University of Chicago, July 7-10, Chicago, IL, U.S.A.
		研討會論文	4	0	100%		
		專書	0	0	100%	章/本	
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力	碩士生	0	0	100%	人次	
		博士生	0	0	100%		

	（外國籍）	博士後研究員	0	0	100%		
		專任助理	0	0	100%		

其他成果 (無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等，請以文字敘述填列。)	無。

	成果項目	量化	名稱或內容性質簡述
科教處計畫加填項目	測驗工具(含質性與量性)	0	
	課程/模組	0	
	電腦及網路系統或工具	0	
	教材	0	
	舉辦之活動/競賽	0	
	研討會/工作坊	0	
	電子報、網站	0	
	計畫成果推廣之參與（閱聽）人數	0	

國科會補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估

   ■達成目標

   □未達成目標（請說明，以 100 字為限）

   　　□實驗失敗

   　　□因故實驗中斷

   　　□其他原因

   說明：

2. 研究成果在學術期刊發表或申請專利等情形：

   論文：□已發表 ■未發表之文稿 □撰寫中 □無

   專利：□已獲得 □申請中 ■無

   技轉：□已技轉 □洽談中 ■無

   其他：（以 100 字為限）

3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）（以 500 字為限）

   就學術成就而言，本計畫所支持之研究已完成數次會議論文之發表。與會過程中收到許多正面回應，並建議投至 A 級以上的期刊。本人已經完成一篇論文並準備投稿。另有兩篇工作論文在撰寫中。

   在技術創新上，本研究利用電腦交易者與真人受測者配合進行市場實驗以控制市場條件，在實驗經濟文獻中屬於相當少見的作法。而本文利用正式的心理測驗取代各式不同但非正式的衡量方法，就本人所知，是實驗經濟學首次利用完整工作記憶評量的研究，為將來可深入探討腦神經機制與決策行為留下了延續研究的空間。之早的文獻研究雖然也有利用工作記憶者，但僅衡量工作記憶中的一個面向，而本實驗測衡量了工作記憶的各個面向。

   就應用價值而言，基於本計畫在雙元預測問題上的結果，本人已著手開始進行產業層級的應用研究，包括了蛛網實驗，以及市場進入賽局（market entry game）的實驗研究。