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To Whom and Where the Hill Becomes Difficult to Climb: Effects of Personality and Cognitive Capacity in Experimental DA Markets

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Abstract

We present an analysis of the data gathered during eight double auction experimental sessions. The aim of this analysis is to assess the effect of the subjects' working memory skills and personality traits on their performances. In the experiments, the subjects had to sequentially face four markets with different structures. We defined the strategies as the combinations of rounds at which the various tokens were bought. We found that the subjects separated into a few classes characterized by different strategies. Moreover, we found that, in general, the group that reached the best strategy was associated with higher working memory test scores than the other groups. However, we also found that the relationship between working memory and performance depends on the market structure. Finally, we found some evidence that, at least within some market structures, personality traits such a hard-working attitude, an easygoing and an outgoing personality were associated with better performance.

Keywords: Experimental Double Auction Markets, Personality Traits, Working Memory, Decision Making.

1. **Introduction**

In this paper we will present an analysis of the data gathered during eight double auction (DA) experimental sessions performed at the National Chengchi University (NCCU) laboratory in the month of June 2010. The aim of this analysis is to gain a deeper understanding of the role that personality traits and cognitive skills (in particular, the subjects' working memory) play in the subjects' learning process.

Since the seminal works of Chamberlin (1948) and Smith (1962), Double Auction (DA) experiments have been performed to test the hypotheses of neoclassical competitive market theory, that is, whether the Efficient Markets Hypothesis is confirmed (or disproved) if the perfectly rational economic agents are substituted by real people when the institutional and informational environments characterizing real double auction markets are reproduced in the laboratory. More recently, human subjects have been substituted by boundedly rational artificial agents in agent-based models of the DA in order to assess under which hypothesis regarding the institutional framework and the agents' behavior the competitive equilibrium could be reached (Gode and Sunder, 1993; Cliff and Bruten, 1997). In another strand of the literature, the introduction of artificial agents has been motivated by the goal to ascertain if, or to what extent, the market efficiency resulting from the artificial agents' behavior (and its evolution) could be compared with that emerging from market experiments with human subjects (Chen and Tai, 2003; Chen et al., 2011). In these studies, the focus has been mainly on the macro-dynamics that emerged from the micro-interactions among the human or artificial players. In this paper, by contrast, we adopt the double auction protocol to study the subjects' learning process and to assess to what extent the different performances that the subjects achieve in the DA experiments are due to their different working memory capacities (WMC) and personality traits.

The influence of working memory on the subjects' decision-making process and strategy development has increasingly become an important subject in the cognitive science and psychology literature in the last ten years. It has been shown that WMC are highly correlated with general intelligence (Kane et al., 2005) and performance in other cognitive domains, such as sentence comprehension (Daneman and Carpenter, 1983) and reasoning (Kyllonen and Christal, 1990). There is evidence that WMC are related to the speed of category learning on a range of categorization tasks (DeCaro et al., 2008; DeCaro et al., 2009; Erickson, 2008; Lewandowsky, 2011). Recently, economists have begun focusing on the empirical relationship between cognitive capacity and economic performance (Cawley et al., 1997; Lynn and Vanhanen, 2002; Weede and Kampf, 2002; Zax and Rees, 2002; Gould, 2005; Jones and Schneider, 2006; Ram, 2007), while experimental economists have started analyzing the effect of cognitive capacity on the outcomes of games such as the Prisoner's

Dilemma Game (Devetag and Warglien, 2008; Hirsh and Peterson, 2009), the Ultimatum Game (Cappelletti et al, 2008), the Dictator Game (Cornelissen et al. 2007; Ben-Ner, Kong and Putterman, 2004; Ben-Ner, Putterman, Kong and Magan, 2004), the Chicken Game (Devetag and Warglien, 2008) and the Trust Game (Ben-Ner and Halldorsson, 2010; Burks et al., 2009). The effect of cognitive capacity on market experiments' outcomes, however, has rarely been addressed, a state of affairs reflecting, to some extent, the widely held assumption (at least among economists) that the market mechanism is so powerful and robust that it leaves no room to participants' intelligence or learning.

Along with WMC, there is ample evidence from economics and psychology that personality traits matter for economic and social outcomes. Phelps (2006) shows that emotions associated with personality traits are involved in learning, attention, and other aspects of cognition. Heckman, Stixrud, and Urzua (2006) show that the power of the personality traits they consider equals or exceeds the predictive power of cognitive traits relatively to schooling, occupational choice, wages, health behaviors, teenage pregnancy, and crime. In the psychology literature, there is substantial evidence on the importance of personality traits in predicting socioeconomic outcomes, including job performance, health, and academic achievement (Barrick and Mount, 1991; Schulz et al., 1996; Hampson et al., 2006; Rothmann and Coetzer, 2003; Hogan and Holland 2003; Robbins et al., 2006; Danner et al., 2001; Weiss and Costa, 2005). Recently, in the field of experimental economics, economists have analyzed the role that personality traits play in various kinds of games (Boone et al., 1999; Hirsh and Peterson, 2009; Swope et al., 2008; Brandstätter and Güth, 2002; Koole et al., 2001; Burks et al., 2003; Ben-Ner, Kong and Putterman, 2004; Ben-Ner, Putterman, Kong and Magan, 2004; Gunnthorsdottir et al., 2002).

In this paper, in order to assess the effect of WMC and personality traits based on their performance in the DA experiments, the human subject plays the role of a buyer in a DA market composed by three other buyers and four sellers that are artificial agents adopting the "Truth Teller" strategy. This protocol ensures that the subjects face the same sequence of bids and asks every trading day, and, most importantly, that for every market structure there is a determined optimal strategy. In this way we can better observe the subjects' learning process and the gap between the strategy they end up adopting and the optimal strategy. This is not the first study in experimental economics that adopts a setup where human subjects and artificial agents interact. Das et al. (2001) report the results of a series of laboratory experiments that allow human subjects to interact with software bidding agents in a CDA. They find that agents consistently obtain significantly larger gains from trade than their human counterparts and persistent far-from-equilibrium trading. Grossklags and Schmidt (2004) conduct an experiment featuring the simultaneous participation of human traders and software agents in order to study how software agents influence the market behavior of human traders. Taniguchi et al. (2005) report and analyze a series of U-Mart experiments, which were conducted by 22 human trader agents and 20 computer programmed software machine agents, finding that while, on average, the machine agents were superior to human agents, the strategy which a human agent adopted was greatly contingent upon his or her character and attitude. The innovative feature of the present paper is that, besides the DA experiments, we conducted a series of working memory tests and personality tests to gather individual data allowing us to assess the relationship between the subjects' performances and their personal characteristics.

2 The DA experimental protocol

In our DA experiments, the subjects had to sequentially face four markets (that we will refer to as M1, M2, M3 and M4) with different structures. In each market, the DA was composed of 30 trading days, each of which was composed of 25 trading rounds. The human subjects were assigned the role of a buyer, participating in a double auction with a set of artificial players composed of three other buyers and four sellers. All the artificial agents made their bid and ask decisions according to the so-called 'Truth Teller' strategy: their bid (ask) was equal to their current highest (lowest) reservation value. During the 25 rounds of each trading day, the players had the opportunity to exchange four tokens each, although only in some of the markets was it profitable for them to buy or sell all four tokens. The trading price for each token exchanged was the average between the highest bid and the lowest ask. If the highest bid (lowest ask) was submitted by more than one buyer (seller), the winner was randomly chosen from these buyers (sellers).

During the 30-trading-day period, the subjects had the chance to learn from their experiences and to discover new and more successful bidding strategies. Since all the other players were truth-tellers, their strategy did not change from one trading day to the next, so that the subjects, on every trading day, faced the same sequences of bids and asks. This experimental feature, on the one hand, was a significant departure from the real-world double auction settings and, on the other hand, allowed us to observe a plausibly simpler and more intelligible learning dynamic that was free from strategic considerations. In particular, under these conditions it is easier to investigate on which conditions and by means of which learning process the subjects converge towards the best bidding strategy.

The experiments' subjects were mostly university students of various Taipei universities, recruited through the NCCU laboratory website. The subjects did not have any prior experience of the double auction trading mechanism. The experiments' rewarding protocol was the following. The experiments were divided into a morning session and an afternoon session. In each session the subjects faced two markets (either M1-M2 or M3-M4). The subjects were paid 200 TWD to participate in each session. They could then gain different sums according to their performances: 150 TWD if they were the best performing trader in the session (among the 8 players involved in the double auction tournament), 80 TWD if they were the second best player, and 40 TWD if they ended up in third place.

The experimental subjects can be divided in two groups: those submitted to the market sequence M1-M2-M3-M4 (Group I) and those submitted to the market sequence M3-M4-M1-M2 (Group II). The total number of subjects in each of the two groups was, respectively, 49 and 53. The four markets were characterized by different structures as shown in Fig. I.

[Figure I]

In this work, we will focus on Group I for the M1 and M2 markets' experimental results and on Group II for the M3 and M4 markets' experimental results. In other words, when analyzing the M1 and M2 markets' experimental results, we will consider only the results obtained in these two markets by Group I and, vice versa, when analyzing the M3 and M4 markets' experimental results, we will consider only the results obtained in these two markets by Group II. The reason why we do not to aggregate the data related to each market across the two groups is that they are not homogeneous in terms of the subjects' experience: the results the Group II subjects obtained in the M1 and M2 markets cannot be compared with those obtained in these two markets by the Group I subjects, as the former had the opportunity to gain some experience of the DA mechanism by tackling the M3 and M4 markets first, and vice versa. Of course, the results in the M2 market were inevitably affected by the experience the Group I subjects gained in the M1 market and, in the same way, the results in the M4 market were affected by the experience the Group II subjects gained in the M3 market. So, in our analysis, we have to take into account the effect that this experience had on the M2 and M4 markets' experimental results.

3 The DA experiments: the markets' structures and results

In M1 the subjects' reservation values for the four tokens are, respectively, 23, 22, 12 and 7. The structure of the M1 market is shown in Fig. II below. Fig. 2 shows the bids, asks and trade prices that characterize the M1 market in the first 11 rounds, if the human subject refrains from trading. In every round, the winning bid and ask is shown in bold (the trading price is the average of these two values).

[Figure II]

We can see from Fig. II that the *best strategy* for Buyer 1 is to buy two tokens in period 7 and 8 (highlighted in Fig. 2), the periods when the trading prices are at their lowest point (11.5). We can see that, in these two periods, the winning bid is 14. This means that if the subject wants to buy two tokens in these two periods, he has to make two bids of 15, buying each token for a trading price of 12 (as the winning asks, in these two periods, are 9 for both tokens). Given the subject's reservation value, this strategy would ensure the subject a profit of (23-12) + (22-12) = 21. The last two trading prices are the hypothetical minimum trading prices, that is, the trading prices that would result from a bid equal to the lowest ask (their hypothetical nature is indicated by the *'I'* within brackets that follows the trading price). We can see from the column of the trading prices that, since all the trading prices are above 12, it is not possible for the subjects to buy the third token, whose reservation value is 12, for a profit. Given that two is the number of tokens Buyer 1 can profitably buy, it is also possible to describe the M1 structure as a bi-dimensional grid where each cell represents a strategy in terms of the rounds in which the two tokens are bought (we recall that in order to buy a token in any given round, the subject needs to submit a bid one unit higher than the highest among the other agents' bids for that round, so every round is associated with a winning bid). Each strategy is associated with a certain total profit, as shown in Fig. III.

[Figure III]

We will call this map the M1 *fitness landscape* (limited to the first 9 rounds in Fig. III). From Fig. III we can see that the M1 fitness landscape has three local optima: the strategy (2, 3), that ensures a profit of 15, the strategy (2, 8), that ensures a profit of 18.5, and the strategy (7, 8), the last one being also the global optimum with a profit of 21 (we will refer to these three strategies, respectively, as L1, L2 and L3). With this definition of the M1 market's strategy space, we can usefully visualize the subjects' strategy in this space and detect 'spatially' separated classes of subjects. Fig. IV below shows the strategies' distribution at the end of the experiment, that is, after 30 trading days.

[Figure IV]

From Figure IV, we can clearly detect four main kinds of subjects according to the location of the strategies they adopted at the end of the experiment in the market's fitness landscape (the integers within brackets in the list below indicate the *number* of subjects in each class):

A. The optimal players, i.e., those who reached strategy L3 (16).
B. The subjects who adopted strategies around L3 (12).
C. The subjects who played the strategy L1 or other strategies around L1 (10). We will refer to these subjects, in this and the other markets, as *risk-averse* subjects, as it seems that these subjects do not want to take the risk implied in waiting for a lower

trading price[1].

D. The subjects who played the strategy L2 or other strategies around L2 (6).

If we sum the numbers within the brackets in the list above, we obtain a total of 44 subjects, while the total number of subjects taking part in the experiment was 49. The remaining 5 subjects were pruned from the dataset as they adopted highly irrational behavior, that is, behavior that can hardly be justified under any kind of assumption, if not a complete misunderstanding of the experiment's protocol or the absence of any motivation in trying to achieve a good performance. For example, two of these subjects simply adopted the 'Truth Teller' strategy from the first trading day on. Two other subjects made apparently random or unreasonably high bids throughout the experiment without any learning process taking place. Another subject, finally, kept buying four tokens up to the last day.

From Figure IV we can see that 36.5% of the subjects (after the pruning) reached the optimal strategy while almost 16% of the subjects ended up playing the sub-optimal strategy (6, 8), and so bought the first token one step too soon. Moreover, we can see that the shares of subjects who ended up around each of the three local optima were, respectively, 22.7%, 13.7% and 63.6%.

In the M2 market, the human subjects' four tokens have reservation values of 79, 76, 76 and 75. Fig. V below shows the bids, asks and trading prices that characterize the M2 market in the first 13 rounds, if the human subject refrains from trading.

[Figure V]

From Fig. V we can see that Buyer 1 can buy only the first token, whose reservation value is 79, for a profit, as subsequently the price in never lower than 76, the second token's reservation value. In this case, at first sight, there seems to be two equivalent best strategies: bidding 77 in round 4, and bidding 76 in any round from round 10 (that is, when all the other buyers' bids of 76 are gone). Both strategies would ensure a trading price of 76, with a profit of 79 – 76 = 3. However, there is a better strategy represented by bidding 76 from round 4 on (until a token is eventually bought). Differing from the strategies considered so far, this strategy requires that the subject does not overbid the other buyers but, instead, places a bid *equal* to the other buyers' bids. We are reminded that, in this case, the winner is randomly chosen: with this strategy, the subject does not know the exact round in which he will be buying the token (it could be any round from 4 to 10, a period highlighted in Fig. V). If the subject buys his token in any round from round 5 to round 10, the trading price will be 76, the

[1] We are, however, aware that this strategy may also have other motivations, such as the subjects' desire to minimize the time devoted to the decision-making process.

same ensured by the two strategies described above. However, in the trading days when he is lucky enough to buy his token in round 4, the trading price will be lower (75.5) so that he will obtain a higher profit. Since the likelihood that the subject will be the winner in round 4 is 1 over 4, the expected profit of this strategy will be equal to 3.125. We have to note that, in order to obtain the highest possible profit, it is important not to bid *after* period 4, but no negative effect would result from the subjects starting bidding 76 *before* round 4 as they would be overbid by the other players and so their bid would have no effect.

The experimental results showed that the subjects could be grouped in a relatively low number of classes according to the strategy they adopted by the end of the experiment:

A. The subjects who reached the best strategy, submitting a bid of 76 from round 4 (or sooner) until they bought one token (19).
B. The subjects who submitted a bid of 77 in round 4 (14).
C. The risk-averse players, who bought their tokens in the first rounds (7).
D. The subjects who made a bid of 76 *after* period 4. Although this strategy allowed them to buy the token at the same trading price as the class B subjects, they delayed with no good reasons for their transactions (3).

In this case, we pruned from the dataset the results of 6 subjects, for reasons similar to those mentioned for the subjects pruned from the dataset of the M1 market's experimental results. The shares of subjects belonging to these four groups are, respectively, 44.2%, 32.5%, 16.3% and 7%.

In the M3 market, the human subjects' four tokens have reservation values of 17473, 17471, 17465 and 17464. Fig. VI below shows the bids, asks and trading prices that characterize the M3 market in the first 16 rounds, if the human subject refrains from trading.

[Figure VI]

From Fig. VI we can see quite easily that the best strategy for Buyer 1 is to buy four tokens from period 13, after all the other buyers have bought their tokens, so as to exploit the absence of competitors, making bids equal to the lowest asks. So, in M3, the optimal strategy is to submit a bid of 42 for all the four tokens. As to the round in which to submit these bids, it is quite irrelevant for the subject's profit, as long as the subject does not wait so long that he will not be able to buy all four tokens (for example, submitting the first winning bid in period 23).

Given that the highest trading price (8753.5) is lower than the lowest reservation price (17464), in this market it is profitable for Buyer 1 to buy all four tokens that the experimental setting allows him to buy. This means that, in considering only the first 16 rounds, there are a total of 1820 possible strategies, each strategy being a combination of four rounds within the first sixteen rounds (and, from the point of view of the results' representation, in this case, it is not possible to conveniently represent neither the market's fitness landscape nor the strategies' distribution by means of a bi-dimensional grid, as we did for the M1 market). Remarkably, notwithstanding the relatively more complex fitness landscape compared to that of M1, also in this case the subjects could be grouped into a relatively low number of classes according to the strategy they adopted by the end of the experiment:

A. The subjects who reached the optimal strategy (35).
B. The subjects who bought their tokens in rounds 5, 6, 7 and 8, or in rounds 7, 8, 9 and 10 (10). We will refer to these subjects, in this and in the M4 market, as the *intermediate* strategy subject, as they wait a few rounds before submitting their bid (in order to submit lower bids), but the time pressure does not allow them to wait until all the other buyers exit the market.
C. The risk-averse players, who bought their tokens in the first rounds, with bids ranging from 17474 to 17472 (6).

In this case, we pruned from the dataset the results of 2 subjects (considering a total of 51 subjects). The shares of subjects belonging to these three groups are, respectively, 68.6%, 19.6% and 11.8%. Another feature of the strategies adopted by the subjects in this market is the uniformity of the bids for the four tokens: the optimal player bid 42, the sub-optimal players bid either 17471 or 17466, and the risk-averse players 17474 or 17472, with a few of them making different bids for different tokens. As a result, the tokens are bought in rounds close to each other, as if in bulk.

Given that this 'bulking' tendency is observed from the first trading days, we can think that buying the tokens as if in bulk, that is, with the same or very similar bids, is a way for the subjects to simplify their task, as it significantly restricts the number of possible strategies. In fact, if the subjects restrict their strategy space to the strategy where the tokens are bought in immediately subsequent rounds, that is (1, 2, 3, 4), (2, 3, 4, 5), and so on, the number of possible strategies is 13 (the number of rounds that it takes for the other three buyers to buy their tokens plus one). Without this constraint the number of possible strategies is 1820, a strategy space far too vast to be exhaustively explored during the thirty trading days. Another explanation for the observed 'bulking' tendency could be the relatively small difference between the reservation values: the highest reservation value is just 0.05% higher than the lowest reservation value. In other words, since the first three digits of the reservation values are the same for all the tokens, it is likely that subjects with limited cognitive and time resources would consider them to be practically equivalent, leading them to make equal bids for all four tokens.

The results of the experiments show that a higher share of subjects reaches the *best strategy* in M3 as opposed to M1 (68.6% and 36.5%, respectively). However, if we look at the shares of subjects who reach either the best strategy or neighboring strategies, the difference is much smaller: almost 68.6% in the M3 market (with very few subjects bidding 43 instead of 42) and 63.6% in the M1 market. So, the real difference between the experiments' results in the M1 and the M3 markets, rather than being the share of subjects who reach the best strategy, is the strategies' distribution around the best strategy, which is more concentrated around the best strategy in M3 and more scattered around it in M1. If we consider the learning dynamics (not shown), we can see that the subjects, although in M3 they stop exploring the strategy space once they discover the best strategy, in M1 almost 50% of those who reach the best strategy keep trying different strategies. So, it seems that in the two markets, subjects will tend to reach the best strategies through different learning processes. While in M1 the subjects seem to learn by means of a trial-and-error process, a process that will eventually make them 'stumble' on the best strategy, in M3 they seem to 'jump' consciously to the best strategy, a cue that they in fact recognize to be the best strategy. The different learning processes leading the subjects to the best strategy in the two markets may be due, in turn, to the different markets' structures. In M1 the best strategy is located in the middle of the fitness landscape and is the point where the sum of the decreasing bids and the increasing asks is at its lowest. As such, the best strategy is hardly detectable by the means of deduction, at least under the given experimental conditions. By contrast, in M3, the best strategy is located at the 'corner' of the fitness landscape, where it stands out quite clearly against the rest of the fitness landscape. As such, it is more easily recognizable by the subjects through logical deduction: as soon as they realize that after round 12 they can buy the token at a trading price equal to the lowest ask, no more exploration of the fitness landscape is required.

Finally, Figure VII shows the bids, asks and trade prices that characterize the M4 market in the first 16 rounds, if the human subject refrains from trading.

[Figure VII]

In this market, the subjects' reservation values were 10518, 10073, 6984 and 6593. As we can see from Fig. VII, the best strategy for Buyer 1 is to buy the first two tokens at steps 7 and 8, by bidding 6988, with trading prices of 4001 and 4002, respectively. The next two lowest asks (and trading prices) are at steps 13 and 14 (4545 and 4547, respectively). Two observations are in order here. First, we can see from Fig. 7 that the highest bid in period 8 is 6985, that would seem to require the subject to bid 6986 (and not 6988). In fact, if the subject bids 6988 in round 7, this would make all the other bids shown in Fig. VII slip one round down and, consequently, the subjects would also have to 'face' the 6987 bid in period 8.

Secondly, if the subjects buy two tokens in rounds 7 and 8, this would make all the other bids slip two rounds down. This means that in rounds 13 and 14 he would have to face the competition of the other buyers. So, the best rounds in which to buy the last two tokens would become rounds 15 and 16, with bids of 4548 and 4550 respectively. To summarize, in the M4 market, the best strategy is to buy the four tokens in rounds 7, 8, 15 and 16 with bids of 6988, 6988, 4548 and 4550. As in the previous three markets, the final strategies adopted can be grouped into relatively low numbers of classes. In this case, we can identity 5 kinds of players:

A. The subjects who reached the best strategy (20).
B. The subjects who adopted the M3 market's best strategy (that is, who bought their tokens in rounds 13, 14, 15 and 16), with bids equal to the four lowest asks as shown in Fig. 5 (16). We will refer to these subjects as *procrastinators*.
C. The risk-averse players, who bought their tokens in the first rounds (6).
D. The 'intermediate' subjects, who adopted either the strategy (4, 5, 6, 7) with four equal bids of 10073, or the strategy (7, 8, 9, 10) with four equal bids of 6988 (5).
E. The subjects who bought each unit by making a bid equal to (or around) the reservation value of the following unit, for example 10073, 6988, 6594 and 4550, buying the four tokens in rounds 4, 8, 12 and 16, respectively (6). We will refer to these subjects as the next-item-reservation-value (NIRV) players.

The shares of subjects belonging to these five groups are, respectively, 38%, 30% and around 10% each for the last three groups. We can see that, apart from the best strategy, which is necessarily different from the previous two best strategies given the different markets' structures, the M4 market structure has elicited the emergence of a sub-optimal strategy, the NIRV, which was not present in the previous two markets. By looking at the strategies adopted by subjects in the M3 market and the subsequent M4 market, we can notice the following facts:

i. the players who reached the optimal strategy in M3 split into two groups of similar size: those who remained trapped in the M3 best strategy (class B in the M4 market) and those who managed to reach the best strategy also in the M4 market;
ii. the class-B subjects in the M3 market split into two groups of similar size in the M4 market: those who adopted a similar 'intermediate' strategy and those who adopted the NIRV strategy (this is true for all the M3 market's class-B subjects except for two of them who reached the optimal strategy in the M4 market);
iii. most of the M3 market's class-C subjects adopted a similar strategy (that is, buying their tokens in the first rounds) also in the M4 market (apart from two players who

switched to the 'intermediate' and the NIRV strategy).

These results allow us to draw the general conclusion that the experience in the M3 market deeply affected the results in the M4 market, although we cannot assess whether this effect was a positive or negative one, as we did not perform experiments where the M4 market was tackled first. In particular, the first point suggests that the group of subjects who reached the best strategy in the M3 market was in fact composed of two kinds of subjects: those who followed the rule '*Buy after the other buyers*' and those who followed the rule '*Buy when the trading prices are at their lowest*' (as we will see in the following section, these two groups are characterized by different WMC). While the two strategies lead to the same result in the M3 market, only the latter also allowed the subjects to reach the best strategy in the M4 market.

The analysis we have conducted so far allowed us to reach the following interesting result: although the markets considered were characterized to different degrees by relatively wide strategies' spaces, the subjects gathered around a few focal points, a behavior that allowed us to separate them into a relatively low number of classes. This may suggest that the subjects, when facing a complex problem, frame it in a limited number of ways and take decisions through a limited number of heuristics, which depend both on the market's structure and the subjects' personal characteristics. In the next section, we will assess whether we can detect differences in the WMT and PT results among the different classes that emerged in the DA experiments.

4 The effect of working memory and personality on DA performance

4.1 The effect of working memory.

More than 500 subjects took five working memory tests (WMT) where they were asked to undertake some tasks such as memorizing series of numbers and letters and performing very basic arithmetic operations. The five working memory tests were:

A. **DgSpan**: the subjects are shown a sequence of numbers and, at the end of the sequence, have to remember it in inverted order.
B. **MuSpan**: the subjects are shown a sequence of numbers in different positions on the screen and, at the end of the sequence they had to sum together the numbers that appeared in the same position.
C. **OpsSpan**: the subjects are shown a series of equations alternating with letters. After each sentence they have to state if it is true or false and, at the end of the series, they have to remember the sequence of letters.

D. **StSpan**: the same as OpsSpan but with sentences instead of sentences.
E. **SSTM**: the subjects are shown a grid with N dots and have to remember the position of the dots in a subsequent blank grid.

We computed and compared the medians of the working memory test scores of each class of subjects identified through the DA experiment, in order to ascertain if the subjects' WMC had any relationship with the subjects' experimental performances. Since we conducted the working memory tests separately from the DA experiments, some of the subjects who participated to the DA experiments did not take the WMT and, consequently, could not be included in this analysis. Moreover, in order not to have classes with too few subjects, we had to regroup some of them. In particular, in the M1 market we regrouped the class-C and class-D subjects into a unique class C (this is why, in Table I, class D is empty for the M1 market). Similarly, in the M4 market, we regrouped class D and class E into a unique class D. As regards the M2 market, we did not consider class D, as it was composed of just 3 subjects. In this case we did not include them in a unique class with the class C subjects as the behavior of these two classes of subjects seemed to be antithetical. Table I below shows the number of subjects included in the WMC analysis for each market and for each (regrouped) class.

[Table I]

Table II below shows the results of this analysis for the M1 market. From Table II we can see a significant correlation between the OpsSpan and the MuSpan scores and the performance in the M1 market.

[Table II]

In particular, class-A subjects seem to have significantly higher medians in these two tests compared to the class-C subjects. Even if the remaining three working memory tests do not seem to be related to the subjects' performance, the difference in the OpsSpan and the MuSpan scores between these two classes is strong enough to make the average WMT scores significantly different. We can notice how the WMT scores are significantly different *between* the groups of subjects who gathered around different local optima, but not *between* those who gathered around the optimal strategy and those reaching the optimal strategy: so, the incapacity of the class-B subjects to reach the best strategy does not seem to be related to their working memory skills.

Table III below shows the results of this analysis for the M2 market. From Table III we can see that the WMT scores of these three classes of subjects do not have significantly different medians. However, there is weak evidence that class-B subjects have a somewhat higher WMC than the class-A subjects. This can be seen both from the direct comparison of the medians of each of the five WMT scores (the first two rows of Table III) and, indirectly, from the fact that all the six *B-vs-C* p-values (the last row of Table III) are lower than the *A-vs-C* p-values (the second to last row of Table III).

[Table III]

One cue that could help us explain this counterintuitive result comes from the observation that most of the subjects reaching the best strategy start bidding 76 from the first period, and they stop bidding once they have bought one token. While the strategy adopted by the class-B subjects required the subjects to pay attention to the round in which the bid was placed (round 4, no sooner and no later), the optimal strategy did not require such a cognitive effort: the subjects could simply play it by following the rule *"Bid 76 from the beginning until one unit is bought"*. Moreover, we can observe that while in the M1 market the classes A and C differ with regard to the *MuSpan* and the *OpsSpan* scores, in the M2 market the *DgSpan* scores seem to be the relevant ones. This result suggests that various aspects of the subjects' WMC, detected by the five working memory tests, play different roles on the subjects' decision-making process depending on the markets' structure the subjects face. In other words, different market structures seem to elicit heuristics requiring different facets of the subjects' WMC.

Table IV shows the results for the M3 market. If we compare the subjects who reached the best strategy (class A) with the risk-averse players (class C), we find that, although three out of five WMT scores have significantly different medians, the difference between the medians of the averages of the WMT scores for these two classes is not significant (with a significance level of 5%).

[Table IV]

Moreover, the WMT score medians of the OpsSpan and the SSTM, and the medians of the averages of the WMT scores are significantly different between the class A subjects and the class B subjects. Note, however, that the former group is associated with *lower* WMT scores than the latter group. So, surprisingly, the WMT results discriminate between the sub-optimal players and the others (the optimal and risk-averse players). Why? The answer to this puzzling result can be found by analyzing the results of the M4 market.

Table V below shows the results of this analysis for the M4 market. Looking at Table V, we can notice how the WMT scores, by and large, tend to be different between the class-A or class-D subjects and class-B or class-C subjects, but *not* between the class-A and class-D subjects or between the class-B and class-C subjects. So, the WMT scores in the M4 market seem to discriminate between two groups of subjects: the optimal and the intermediate subjects (class A and D), on the one hand, and the procrastinators and the risk-averse players (class B and C), on the other.

[Table V]

If we are reminded that the analysis of the DA results showed that class A of the M3 market was for the most part composed by class-A and class-B subjects of the M4 market, we can understand, at this point, why in the M3 market we cannot find any difference between the medians of the averages of the WMT scores of class A and class C in this market: the group of the optimal players was composed both of high WMC subjects (class A in the M4 market) and low WMC subjects (class B in the M4 market) and this brought down the median of the WMT scores of class A, making it indistinguishable from the median of the WMT scores of class C.

This finding tells us that the M3 market's structure is such that, on one hand, having a high working memory is not necessary to reach the optimal solution as in this market we observed that both high and low WMC subjects reached the best strategy: evidently, low-working-memory heuristics, such as trial-and-error learning, are sufficient to find the best strategy in M3. On the other hand, a high working memory does not guarantee the best performance, as we observe that a few high WMC subjects failed to reach the best strategy both in the M3 market (the class B) and in the M4 market (the class D).

4.2 The effect of personality traits.

More than 203 subjects took the personality test (PT). In these tests, the subjects were presented with 131 adjectives, each of which has a certain relationship with the following personality attributes:

1. Smart (**S**);
2. Hard-working (**HW**);
3. Easygoing (**EG**);
4. Honest (**H**);
5. Outgoing (**OG**);
6. Forthright (**F**);
7. Optimistic (**O**).

The subjects had to rate themselves on a scale from 1, if they thought that the adjective did not at all describe their personality, to 6, if they thought that the adjective perfectly described their personality. As for the WMT, we conducted the personality tests separately from the DA experiments so that some of the subjects who participated to the DA experiments did not take the PT tests and could not be included in this analysis. Table VI below shows the number of subjects included in the PT analysis for each market and for each class.

Table VII shows the medians and the p-values of the one-tailed Mann-Whitney U test of the PT scores of the M1 market's classes of subjects. From Table VII it is possible to see that the personality trait that seems to give rise to the different behavior between the optimal players and the class C subjects in the M1 market is the hard-working attitude, while the optimal players have a higher PT score in the outgoing personality trait compared to the subjects adopting neighboring strategies. The outgoing personality trait, also referred to as *extraversion*, is one on the Big Five personality traits of the Five Factor Model.

[Table VI]

Extraversion is defined as 'the act, state, or habit of being predominantly concerned with and obtaining gratification from what is outside the self' (Merriam Webster Dictionary).

[Table VII]

A study by Depue and Collins (1999) shows that extraversion is linked to higher sensitivity of the mesolimbic dopamine system to potentially rewarding stimuli. In other words, extroverts tend to feel more intensely than introverts the excitement of a potential reward and, as a consequence, can more easily learn the contingencies for positive reinforcement, since the reward itself is experienced as greater. So, one possible explanation for the link between the outgoing personality and the M1 market's experimental results could be related to the different motivation levels of the subjects: class B subjects seem to be diligent enough to reach strategies near the global optimum but lack the additional drive that allows the class A subjects to reach the best strategy.

Table VIII shows the medians and the p-values of the one-tailed Mann-Whitney U test for the PT scores of the M2 market's classes of subjects.

[Table VIII]

From Table VIII it is possible to see that the personality trait that the class-B and the class-C subjects in the M2 market are characterized by gives rise to significantly different scores in the hard-working trait, a finding that confirms the importance of this personality trait in the DA experiments' performances. If we compare the hard-working attitude of the class-B subjects with that of the class-A subjects, we see that the former seem to be higher than the latter (although this is true only at a significance level of 10%), a finding that is consistent with the hypothesis advanced in the previous section that the strategy adopted by the class-B subjects is more difficult to find and follow than the optimal strategy.

Table IX shows the medians and the p-values of the one-tailed Mann-Whitney U test for the PT scores of the M3 market's classes of subjects.

[Table IX]

Since the WMT analysis, in the previous section, showed that class A was in fact composed of two distinct groups characterized by different WMC levels, we separated this class into two distinct classes: class A1, composed of those subjects who reached the best strategy also in the M4 market, and class A2, composed of those subjects who did not reach the best strategy also in the M4 market (and kept adopting the best strategy in the M3 market). These classes are composed of 15 and 13 subjects, respectively. In this case, the hard-working attitude seems to be the personal trait that discriminates between the two high WMC groups of subjects that emerged in the M3 market: those who found the best strategy (A1) and those who failed to find it (B). Moreover, among the subjects who found the best strategy, the high WMC subjects (A1) have a higher score for the easygoing attitude trait compared to the low WMC subjects (A2). This is the only case where the easygoing attitude seems to have some relationship with the DA experimental results. A possible explanation for this finding is that people with a higher easygoing attitude (personality type B, in the *Type A and Type B Personality Theory*) can stand higher levels of pressure and, in particular, are less stressed by the time pressure. So, these subjects may have given themselves more time to think and explore the strategy space than the subjects characterized by a lower easygoing attitude, an explanation consistent with the findings of Bingham and Hailey (1989). While this different attitude did not make any difference in the context of the M3 market (as both the A1 and the A2 subjects reached the best strategy in this market), it could have been, together with the different WMC levels, a factor that caused these two groups of subjects to reach different strategies in the M4 market. Finally, we observe that the two low WMC subjects (that is, the A2 and the C class) are characterized by significantly different levels of optimism. However, this fact is not easy to interpret as, contrary to what one may expect, the former have a *lower* level of optimism than the latter.

Table X shows the medians and the p-values of the one-tailed Mann-Whitney U test for the PT scores of the M4 market's classes of subjects.

[Table X]

In this case, the hard-working attitude discriminates between the class-C and the class-D subjects. However, the former has a higher hard-working attitude than the latter, a finding that is not easy to interpret if we consider that the subjects in class C are those who bought their tokens as soon as possible. Interestingly, the hard-working attitude seems to be a relevant factor behind the different performances of subjects with *similar* levels of WMC: class-A subjects seem to have a higher hard-working attitude than class-D subjects and, similarly, class-B subjects seem to have a higher hard-working attitude than class-D subjects, although in both cases with a significance level of 10% (with p-values of 0.067 and 0.057, respectively).

5 Conclusions

From a general point of view the analysis of the experimental data showed that the subjects' decision-making process and, in particular, the subjects' performance in the DA experiments depend both on the subject's characteristic and the particular market's structure.

In particular, our analysis showed that the WMC do matter to the DA experimental outcomes: in the M1, M3 and M4 markets (with a significance level of 5%) and in the M2 market (with a significance level of 10%) two or more classes of subjects were associated with significantly different WMT scores. This is not to say, however, that the subjects with higher WMC were *always* associated with better performances: in fact, while in the M1 and the M4 markets the subjects who reached the best strategy were associated with WMT scores higher than those of other classes of subjects, in the M2 and M3 markets the class of the 'optimal' subjects was in fact associated with WMT scores *lower* than the 'sub-optimal' class-B subjects. This means that, in some markets, having high WMC is not a necessary condition to reach the optimal strategy, as even subjects with low WMC can reach it, presumably by adopting simple heuristics that do not require high levels of cognitive skills. On the other hand, our analysis showed that there are classes of subjects (i.e., class B in the M1, M2 and M3 markets and class D in the M4 market) that, in spite of being characterized by high WMT scores, fail to reach the best strategy. This means that having high WMC is not a sufficient condition for having a good performance: other factors, such as the subjects' personality traits, are also important. So, we can say that although the WMC seem to have, by and large, a positive effect on the subjects' performances, its importance relative to other factors, such as the personal traits, seems to depend on the market's structure.

This result is consistent with previous works on the effect of the WMC on various performances' indexes. Devetag and Warglien (2003), in conducting experiments on a set of well-known games whose solution concepts require the application of some paradigmatic forms of strategic reasoning (such as iterated dominance and backward induction), show the presence of a significant and positive correlation between subjects' short-term memory score and conformity to standard game-theoretic prescriptions. In a subsequent paper (Devetag and Warglien, 2008) the same authors find that differences in the relative ability to correctly represent the structure of strategic interaction appears to be (weakly) correlated with differences in short-term memory capacity. A few works (see Warner and Pleeter 2001, Fredrick 2005, Benjamin et al. 2006) have shown that persons with higher cognitive ability tend to be more patient and less impulsive. Burks et al. (2009) find a strong and significant relationship between an individual's cognitive skills and preferences. In particular, individuals with better cognitive skills are more patient, in both the short and long run, have a greater willingness to take calculated risks and, in a sequential Prisoner's Dilemma game, more accurately forecast others' behavior. Finally, they find that the individual's cognitive skills strongly predict perseverance on the job. They conclude that higher cognitive skills systematically affect preferences and choices in ways that favor economic success.

As regards the effect of the personality traits on the DA outcomes, our analysis has shown that among all personality traits the hard-working attitude seems to be the trait most often associated with a good performance: in the M1, M2 and M3 markets, at least two classes have significantly different hard-working attitudes. Moreover, in the M1 and M3 markets, the class of subjects who reach the best strategy is associated with a hard-working attitude that is higher than that of another 'sub-optimal' class.

If we consider the hard-working attitude to be equivalent to *conscientiousness* in the 'Big Five' Factors Model, our result is consistent with the findings of previous work focusing on the effect of personality traits on economic outcomes. Barrick and Mount (1991), in investigating the relationship of the "Big Five" personality dimensions to three job performance criteria for five occupational groups, find that *conscientiousness* shows a consistent relationship with all job performance criteria for all occupational groups, while *extraversion* is a valid predictor for occupations involving social interaction. Hampson et al. (2006) find that childhood personality traits were significantly associated with smoking, alcohol use, body mass index (BMI) and self-rated health, 40 years later. In particular, childhood *conscientiousness* was associated with less adult smoking and better adult self-rated health and, for women only, with lower adult BMI. Finally, Robbins et al. (2006), in controlling for institutional effects and traditional predictors, tested the effects of motivational and skill, social, and self-management measures on academic performance and retention. They found that Academic Discipline (an index closely related to *conscientiousness*) was incrementally predictive of academic performance and retention. Moreover, Social Activity (i.e., *extraversion*) and Emotional Control (inversely related to *neuroticism*) also helped predict academic performance and retention.

The relevance of other personality traits seems to be conditional on the structure of the market: the outgoing attitude (equivalent to *extraversion* in the 'Big Five' Factors Model) seem to be relevant in the M1 market (and in the M3 market with a significance level of 10%) while the easygoing attitude seem to exert its effect on the M3 market's outcomes (and in the M2 and M4 markets with a significance level of 10%).

Finally, even though in this paper we considered the working memory skills and the personality traits separately, they are likely to interact and to co-determine the subjects' performances. In fact, the subject's motivation results from a comparison of the effort they have to exert to solve a particular task and the experiment's incentives, as they are perceived. Whereas the first factor depends on the subject's cognitive skills, the second factor depends on the subject's personality. So, given a certain incentive's structure, subjects with lower cognitive skills, that is, with a higher cost associated with the problem-solving activity, and with a less 'competitive' attitude, are less likely to exert the effort it takes to reach a good performance. In other words, subjects with lower WMC need higher levels of incentives in order to engage in the decision-process required to obtain a good performance, compared to subjects with high WMC. In fact, we can think of the hard-working attitude, which our analysis showed to be the single most important personality trait, as a measure of the subjects' responsiveness to incentives, with the subjects with a high score for this personality trait being the most responsive ones. More experiments are needed in order to ascertain the extent to which the poor performance is due to a lack of motivation rather than a lack of the minimal cognitive skills' level necessary to succeed.

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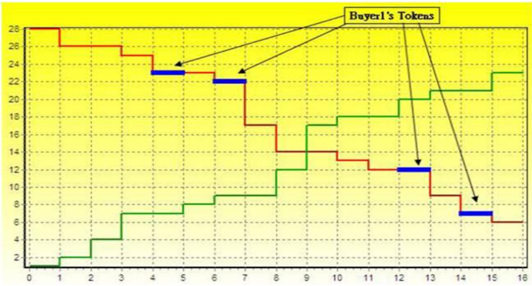
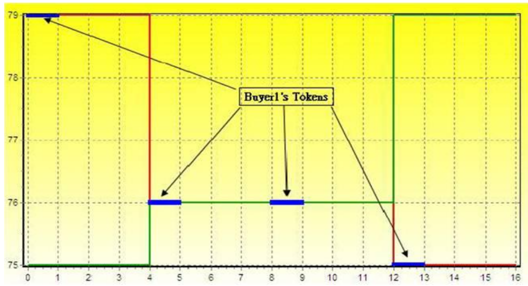
Fig. I: The four markets of the DA experiments.



M1



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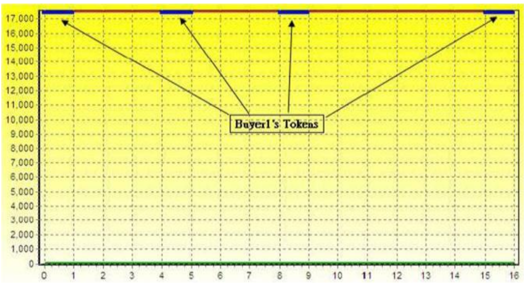

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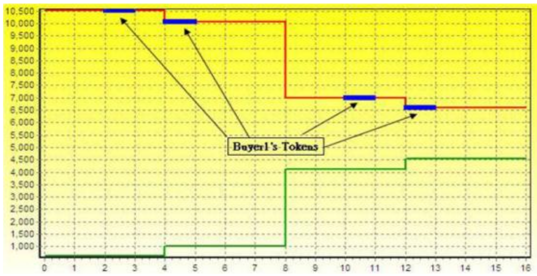

M4

Fig. II: The M1 market artificial agents' bids and asks, and trading prices.

Step	Buyer 1	Buyer 2	Buyer 3	Buyer 4	Seller 1	Seller 2	Seller 3	Seller 4	Price
1	-	**28**	23	26	2	8	**1**	7	14.5
2	-	**26**	23	26	**2**	8	4	7	14
3	-	17	23	**26**	7	8	**4**	7	15
4	-	17	23	**25**	**7**	8	9	7	16
5	-	17	**23**	14	17	8	9	**7**	15
6	-	**17**	14	14	17	**8**	9	9	12.5
7	-	13	14	**14**	17	12	**9**	9	11.5
8	-	13	**14**	12	17	12	18	**9**	11.5
9	-	**13**	9	12	17	**12**	18	20	12.5
10	-	-	9	12	17	21	18	20	17(I)
11	-	-	9	12	17	21	18	20	17(I)

Figure III: The M1 markets' fitness landscape.

	2	3	4	5	6	7	8	9
1	14.5	14.5	13	13.5	14	16.5	18	16.5
2		**15**	13.5	14	14.5	17	**18.5**	17
3			12.5	13	13.5	16	17.5	16
4				12	12.5	15	16.5	15
5					13.5	16	17.5	16
6						18.5	20	18.5
7							**21**	19.5
8								19.5

Figure IV: The strategies' distribution on the 30th trading day (%).

	2	3	4	5	6	7	8	9
1	16.2	3.6				2.0	4.5	1.8
2		2.0				2.7	2.7	
3			0.9					
4								
5								
6						4.5	15.9	
7							36.5	4.5
8								2.2

Fig. V: The M2 market artificial agents' bids and asks, and trading prices.

Step	Buyer 1	Buyer 2	Buyer 3	Buyer 4	Seller 1	Seller 2	Seller 3	Seller 4	Price
1	-	**79**	79	79	**75**	75	75	75	77
2	-	76	**79**	79	76	**75**	75	75	77
3	-	76	76	**79**	76	76	**75**	75	77
4	-	**76**	76	76	76	76	76	**75**	75.5
5	-	**76**	76	76	**76**	76	76	76	76
6	-	75	**76**	76	**76**	76	76	76	76
7	-	75	**76**	76	79	**76**	76	76	76
8	-	75	75	**76**	79	**76**	76	76	76
9	-	75	75	**76**	79	79	**76**	76	76
10	-	75	75	75	79	79	76	76	76(I)
11	-	75	75	75	79	79	79	76	76(I)
12	-	75	75	75	79	79	79	76	76(I)
13	-	75	75	75	79	79	79	79	79(I)

Fig. VI: The M3 market artificial agents' bids and asks, and trading prices.

Step	Buyer 1	Buyer 2	Buyer 3	Buyer 4	Seller 1	Seller 2	Seller 3	Seller 4	Price
1	-	17473	**17473**	17473	**33**	34	34	34	8753
2	-	**17473**	17470	17473	**34**	34	34	34	8753.5
3	-	17470	17470	**17473**	40	**34**	34	34	8753.5
4	-	17470	17470	**17471**	40	34	**34**	34	8752.5
5	-	**17470**	17470	17465	40	34	34	**34**	8752
6	-	17465	**17470**	17465	40	**34**	34	34	8752
7	-	**17465**	17465	17465	40	39	34	**34**	8749.5
8	-	**17465**	17465	17465	40	39	**34**	40	8749.5
9	-	-	**17465**	17465	40	39	**39**	40	8752
10	-	-	**17465**	17465	40	**39**	42	40	8752
11	-	-	-	**17465**	40	42	42	**40**	8752.5
12	-	-	-	**17465**	**40**	42	42	42	8752.5
13	-	-	-	-	42	42	42	42	42(I)
14	-	-	-	-	-	42	42	42	42(I)
15	-	-	-	-	-	-	42	42	42(I)
16	-	-	-	-	-	-	-	42	42(I)

Figure VII: The M4 market artificial agents' bids and asks, and trading prices.

Step	Buyer 1	Buyer 2	Buyer 3	Buyer 4	Seller 1	Seller 2	Seller 3	Seller 4	Price
1	-	10519	10516	**10521**	622	622	**618**	619	5569.5
2	-	**10519**	10516	10071	622	622	1014	**619**	5569
3	-	10072	**10516**	10071	**622**	622	1014	1016	5569
4	-	**10072**	10071	10071	1013	**622**	1014	1016	5347
5	-	6981	**10071**	10071	1013	**1010**	1014	1016	5540.5
6	-	6981	6985	**10071**	**1013**	4101	1014	1016	5542
7	-	6981	6985	**6987**	4102	4101	**1014**	1016	4000.5
8	-	6981	**6985**	6590	4102	4101	4100	**1016**	4000.5
9	-	**6981**	6589	6590	4102	4101	**4100**	4100	5540.5
10	-	**6593**	6589	6590	4102	4101	4545	**4100**	5346.5
11	-	-	6589	**6590**	4102	**4101**	4545	4550	5345.5
12	-	-	**6589**	-	**4102**	4548	4545	4550	5345.5
13	-	-	-	-	4547	4548	4545	4550	4545(I)
14	-	-	-	-	4547	4548	-	4550	4547(I)
15	-	-	-	-	-	4548	-	4550	4548(I)
16	-	-	-	-	-	-	-	4550	4550(I)

Table I: Number of subjects included in the WMC analysis.

	A	**B**	**C**	**D**
M1	15	11	14	-
M2	13	12	6	-
M3	29	9	6	-
M4	17	13	6	10

Table II: WMT score medians (and p-values of the one-tailed Mann-Whitney U test) for M1 for three kinds of players.

	DgSpan	MuSpan	OpsSpan	StSpan	SSTM	Average
A	0.941	0.847	0.843	0.838	0.895	0.842
B	0.917	0.773	0.776	0.833	0.871	0.792
C	0.928	0.718	0.765	0.804	0.882	0.776
			p-values			
A vs B	0.124	0.124	0.147	0.470	0.086	0.159
A vs C	0.232	**0.011**	**0.003**	0.232	0.398	**0.01**
B vs C	0.457	0.179	0.242	0.314	0.087	0.194

Table III: WMT score medians (and p-values of the one-tailed Mann-Whitney U test) for M2 for the three classes.

	DgSpan	MuSpan	OpsSpan	StSpan	SSTM	Average
A	0.932	0.758	0.804	0.837	0.882	0.804
B	0.955	0.841	0.818	0.862	0.885	0.840
C	0.850	0.752	0.797	0.798	0.888	0.777
			p-values			
A vs B	0.167	0.167	0.479	0.354	0.479	0.167
A vs C	**0.016**	0.399	0.5	0.131	0.432	0.304
B vs C	**0.001**	0.135	0.262	0.069	0.292	0.083

Table IV: WMT score medians (and p-values of the two-tailed Mann-Whitney U test) for M3's players' types.

	DgSpan	MuSpan	OpsSpan	StSpan	SSTM	Average
A	0.946	0.710	0.807	0.841	0.879	0.795
B	0.951	0.832	0.879	0.886	0.917	0.869
C	0.883	0.665	0.659	0.653	0.840	0.676
			p-values			
A vs B	0.362	0.056	**0.036**	0.194	**0.024**	**0.03**
A vs C	**0.024**	0.335	**0.011**	**0.033**	0.131	0.064
B vs C	**0.029**	0.124	**0.001**	**0.015**	**0.015**	**0.005**

Table V: WMT score medians (and p-values of the two-tailed Mann-Whitney U test) for the M4 market classes.

	DgSpan	MuSpan	OpsSpan	StSpan	SSTM	Average
A	0.959	0.804	0.847	0.869	0.905	0.848
B	0.930	0.589	0.758	0.800	0.856	0.732
C	0.879	0.584	0.648	0.629	0.835	0.646
D	0.944	0.847	0.850	0.890	0.902	0.859
			p-values			
A vs B	**0.031**	**0.001**	**0.005**	**0.049**	**0.009**	**0.001**
A vs C	**0.014**	**0.017**	**0.009**	**0.006**	**0.034**	**0.003**
A vs D	0.137	0.5	0.461	0.365	0.441	0.365
B vs C	0.07	0.5	0.151	**0.048**	0.247	0.196
B vs D	0.251	**0**	**0.004**	**0.02**	**0.02**	**0.001**
C vs D	**0.042**	**0.005**	**0.01**	**0.003**	**0.042**	**0.01**

Table VI: Number of subjects included in the PT analysis.

	A	B	C	D
M1	15	11	16	-
M2	17	14	7	-
M3	28	9	6	-
M4	17	12	6	10

Table VII: PT score medians (and p-values of the one-tailed Mann-Whitney U test) of the M1 market classes.

	S	HW	EG	H	OG	F	O
A	87.33	73.67	77.87	87.20	78.07	68.73	56.13
B	83.55	74.45	81.27	87.55	67.18	66.91	54.09
C	82.31	68.31	76.81	85.75	72.94	68.63	53.44
p-values							
A vs B	0.429	0.39	0.185	0.429	**0.046**	0.245	0.39
A vs C	0.293	**0.034**	0.5	0.348	0.229	0.438	0.206
B vs C	0.442	0.111	0.264	0.349	0.133	0.153	0.314

Table VIII: PT score medians (and p-values of the one-tailed Mann-Whitney U test) of the M2 market classes.

	S	HW	EG	H	OG	F	O
A	81.00	61.54	64.71	80.33	65.84	64.77	49.44
B	81.79	76.14	82.86	86.86	72.93	66.36	54.57
C	86.71	66.29	75.29	87.57	69.86	71.86	53.86
				p-values			
A vs B	0.097	0.09	0.194	0.392	0.173	0.135	0.392
A vs C	0.278	0.183	0.278	0.367	0.183	0.343	0.438
B vs C	0.12	**0.025**	0.08	0.471	0.331	0.19	0.471

Table IX: PT scores' medians (and p-values of the one-tailed Mann-Whitney U test) of the M3 market classes.

	S	HW	EG	H	OG	F	O
A1	88.13	74.87	83.47	86.07	77.67	65.13	54.13
A2	82.85	71.54	74.15	84.38	69.08	66.08	48.38
B	80.89	64.89	85.00	84.78	74.67	64.22	52.44
C	80.00	72.33	78.00	81.50	75.83	67.50	55.33
			p-values				
A1 vs A2	0.164	0.241	**0.047**	0.384	0.057	0.213	0.068
A1 vs B	0.232	**0.026**	0.331	0.442	0.232	0.442	0.442
A1 vs C	0.096	0.298	0.325	0.125	0.41	0.201	0.44
A2 vs B	0.384	0.087	0.051	0.335	0.289	0.335	0.154
A2 vs C	0.304	0.399	0.275	0.247	0.173	0.304	**0.04**
B vs C	0.284	0.101	0.246	0.324	0.366	0.366	0.366

Table X: PT score medians (and p-values of the one-tailed Mann-Whitney U test) of the M4 market classes.

	S	HW	EG	H	OG	F	O
A	84.47	73.24	83.76	84.59	78.00	64.41	53.65
B	83.67	71.42	75.17	83.92	70.00	66.67	49.25
C	77.67	77.50	80.17	86.17	73.33	67.50	53.50
D	86.40	65.60	79.60	85.90	74.30	65.40	52.40

p-values

	S	HW	EG	H	OG	F	O
A vs B	0.316	0.397	0.061	0.448	0.101	0.137	0.127
A vs C	0.083	0.226	0.187	0.446	0.317	0.083	0.419
A vs D	0.461	0.067	0.347	0.384	0.26	0.422	0.403
B vs C	0.135	0.057	0.292	0.262	0.428	0.325	0.116
B vs D	0.303	0.149	0.259	0.259	0.218	0.303	0.182
C vs D	0.066	**0.007**	0.299	0.376	0.376	0.337	0.417

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