

INNOVATION, ENTRY INTO MULTIPLE MARKETS AND UNOBSERVED HETEROGENEITY*

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Abstract

This paper considers an experimental market entry game, where the decision problem involves several heterogeneous markets and players have an opportunity to enter several markets simultaneously. We find that groups fail to coordinate on any of the multiple pure strategy Nash equilibria by exhibiting excess entry in the majority of rounds. The likelihood of overentry depends on the market capacity and characteristics of the experimental markets. We also find that, on average, the behavior of the individual participants can be reconciled with the mixed strategy equilibrium prediction. Yet, this prediction fails to account for the differences in the individual profiles. By conducting an econometric estimation that accounts for the unobserved heterogeneity, we show that market capacity, expectations about the number of entrants, the amount of payoff from the previous period and the history of over- or underentry have significant impact on the individual action choice.

Keywords: Market entry games, coordination failure, Nash equilibrium solution, unobserved heterogeneity

JEL classification: C72, C92, D83, D91

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1. Introduction

Excess entry is one of the widely researched explanations of the empirical observation that new businesses tend to exhibit high rates of failure (e.g. Camerer and Lovo, 1999; Bolger et al., 2008). While new business failure is observed in many competitive industries (e.g. Dunne et al., 1988), it is especially apparent on innovative markets with relatively small capacities and relatively high entry costs (e.g. Tucker, 2002). By imitating market entry situations under controlled conditions in the laboratory, experimental studies have analyzed individual and group behavior in an iterated market entry game (MEG). Yet, to date, economic research has primarily concentrated on testing various learning models using the data obtained either in a single market setting or in a multiple market setting, when markets are homogeneous in their entry costs.

However, new businesses often face choices involving multiple heterogeneous markets. They have to decide not only whether to enter a certain market or which market to enter, but also how many markets to enter. For example, in the automotive industry, a new start-up has a threefold choice. First, it may opt for entering an innovative high-performance car market with low market capacity and significant entry costs (e.g. Ferrari S.p.A.). Second, it may decide to concentrate on producing mainstream vehicles (e.g. Mazda) by entering a family car market. Finally, it may enter both markets simultaneously (e.g. Mercedes).

The purpose of this paper is to analyze entry decisions and coordination in the presence of multiple heterogeneous markets using an experimental MEG, where players have an opportunity to enter several markets simultaneously. We explore whether experimental participants behave according to the predictions of the Nash equilibria in pure and mixed strategies. We also identify factors that have an impact on the individual decisions using econometric analysis that accounts for the unobserved heterogeneity. We particularly investigate whether and to what extent beliefs about the number of entrants into the market and individual risk attitudes influence entry decisions.

Recent studies in economics and psychology have investigated tacit coordination in an iterated MEG with complete information (e.g. Kahneman, 1988; Selten and Güth, 1992; Rapoport, 1995; Rapoport et al., 1998; Camerer and Lovo, 1999). In a standard MEG, N players choose simultaneously and without communicating whether to enter a market or not. The size of the market (market capacity) is a preannounced number c . All players receive an initial endowment K . If players do not enter, they keep their initial endowment. If E players

enter the market, then each of them receives $\pi = K + r \cdot K \cdot (c - E)$, where r is a positive constant multiplier and $r \cdot K > 0$.

When $N > c > 0$ MEG has multiple pure strategy Nash equilibria. These equilibria cannot be ranked in terms of the payoff dominance. Moreover, there is no focal principle (Schelling, 1980) in the game, which would help the players coordinate on a particular equilibrium. Therefore, the usual hypothesis is to expect coordination failures in such a game.

Nevertheless, the majority of experimental studies report high coordination levels. Particularly, Kahneman (1988) observes that the number of entrants E in MEG falls within the interval $[c - 2, c + 2]$. Rapoport (1995) documents that while participants tend to enter too frequently in the beginning of the experiment, the number of entrants converges to c in the iterated play. Rapoport et al. (2002) find that high coordination levels in the aggregate could be rationalized by the Nash equilibrium solution and employ reinforcement-based learning model to account for the differences in the individual behavior. Erev and Rapoport (1996) show that in MEG participants quickly converge to the equilibrium even when they do not know the payoff rule. Yet, Camerer and Lovo (1999) document coordination failures when participants self-select into the experiment based on their relative skill-perception (when participants are overconfident about their abilities). Fischbacher and Thöni (2008) observe inefficiently many entries into a “winner-take-all” market and find that excess entry intensifies as the group of potential entrants increases.

Rapoport et al. (2000) develop a two market entry game (TMEG) to study a situation when agents are trying to avoid congestion. In their study, Rapoport et al. (2000) look at markets with different market capacities, but identical entry costs of zero. Players do not have an opportunity to enter several markets simultaneously and have to choose which of the two markets they want to enter (if any). Like in the previous studies, Rapoport et al. (2000) document high levels of coordination. Selten et al. (2004) look at a route choice behavior in a TMEG setting, where players do not have an opportunity to stay out.

This paper builds upon Camerer and Lovo (1999) and Rapoport et al. (2000) experimental designs and extends Rapoport et al. (2002) analysis of individual heterogeneity in MEG by accounting for the unobserved heterogeneity of players. We construct two markets. These markets are heterogeneous not only in their capacity, but also in their entry costs and potential payoffs. Market 1 (innovative market) has a relatively low market capacity, relatively high cost of entry and high potential payoff. Market 2 (less innovative market) is characterized by the relatively high market capacity, relatively low cost of entry and low potential payoff. All players have a fourfold action space: they can (a) enter Market 1 and stay out of Market 2, (b) enter Market 2 and stay out of Market 1; (c) enter both markets simultaneously and (d) stay out of both markets.

This study contributes to the existing literature on market entry in several ways. First, combining the design of a simple market entry game with the multiple heterogeneous market structure, we consider a situation when players have an opportunity to enter multiple competitive markets with different entry costs and potential payoffs. Second, our experimental design allows players to enter several markets simultaneously. Finally, rather than testing predictive and explanatory power of the learning theories, in this paper we explore the determinants of the individual action choice by accounting for the unobserved heterogeneity of the experimental participants using panel econometric estimation.

We find that groups fail to coordinate on the pure strategy Nash equilibria and tend to overenter into the markets in the majority of experimental rounds. Moreover, they do not seem to converge to equilibrium predictions in the iterated play. Even though we observe coordination failure at a group level, on average, individual participants appear to play according to the predictions of the mixed strategy equilibrium. Yet, this equilibrium does not account for the differences in the individual profiles of the experimental participants.

Previous research has documented that the number of entrants into a market is highly correlated with the market capacity (e.g. Kahneman, 1988; Rapoport 1995). This paper suggests another important implication of market properties on entry. We find that there is a relationship between the market capacity and the propensity to observe overentry, which is contingent on the characteristics of the market. Particularly, the lower the capacity of Market 1 (with low capacity, high entry cost and high potential payoff) the more likely the groups are to exhibit overentry into Market 1. However, the higher the capacity of Market 2 (with high capacity, low entry cost and low potential payoff) the more likely the groups are to exhibit overentry into Market 2.

In order to disentangle the determinants of the individual decisions, we use a random intercept multinomial logit regression (e.g. Haan and Uhlendorff, 2006). The estimation results suggest significant variability in entry choices due to unobserved heterogeneity. Participants appear to take into account their expectations about the number of entrants into each of the markets. Notably, the lower the number of expected entrants, the more likely the participants are to enter. The propensity of entering a market increases if participants did not observe overentry into a market in the previous period of the game. The amount of payoff from the previous period also has a significant impact on participants' entry decisions.

Interestingly, the lower the capacity of Market 1, the more likely the participants are to enter Market 1 and both markets simultaneously. However, the higher the capacity of Market 2, the more likely the participants are to enter Market 2. We also find that participants who enter two markets simultaneously appear to be significantly more risk seeking than those who stay out of any of the markets. In addition, our results provide some evidence that experimental participants generally underestimate the number of entrants into both markets.

The remainder of this paper is structured as follows. Section 2 describes the experimental design and the laboratory procedure. Results of the analysis are presented in Section 3. Finally, Section 4 concludes with a general discussion.

2. The Experiment

2.1 Experimental Design

In the experiment N players participate in the iterated TMEG. In the beginning of every period, each player receives an initial endowment $K > 0$. After that, all players are presented with two markets. Market 1 has a relatively low capacity c_{M1} and a relatively high cost of entry $\alpha \in (0, K)$. Market 2 has a relatively high capacity $c_{M2} \geq c_{M1}$ and a relatively low cost of entry $\beta \in (0, K)$.¹ The cost of entry into Market 1 (α) is significantly larger than the cost of entry into Market 2 (β), i.e. $\alpha \gg \beta$.²

Players choose simultaneously and without communicating with each other among the following four actions:

- $M1$: enter Market 1, stay out of Market 2;
- $M2$: enter Market 2, stay out of Market 1;
- $M1 + M2$: enter both Market 1 and Market 2 simultaneously;
- OUT : stay out of both markets.

Therefore, each player has a fourfold action space $A \in \{M1, M2, M1 + M2, OUT\}$.

If E_{M1} players choose action $M1$, E_{M2} opt for action $M2$, and E_{M1+M2} players take action $M1 + M2$, then each player has the following expected payoff structure depending on the chosen action:

- $M1$: $\pi = K - \alpha + r_{M1} \cdot K \cdot (c_{M1} - E_{M1} - E_{M1+M2})$;
- $M2$: $\pi = K - \beta + r_{M2} \cdot K \cdot (c_{M2} - E_{M2} - E_{M1+M2})$;
- $M1 + M2$: $\pi = K - \alpha - \beta + r_{M1} \cdot K \cdot (c_{M1} - E_{M1} - E_{M1+M2}) + r_{M2} \cdot K \cdot (c_{M2} - E_{M2} - E_{M1+M2}) + s$;
- OUT : $\pi = K$,

where $r_{M1} > 0$ and $r_{M2} > 0$ are positive constant multipliers for Market 1 and Market 2, respectively. We assume that the innovative market provides a higher potential payoff than the less innovative market. Therefore, in our experimental design, Market 1 has a higher positive multiplier than Market 2 (i. e. $r_{M1} > r_{M2}$).

¹ In the experiment we also consider a case when Market 1 and Market 2 have equal capacities.

² In the experiment, α was ten times larger than β .

We construct two treatments. In the *BASELINE* treatment entry to both markets does not result in an additional spillover from one market to the other. In the *SPILLOVER* treatment we consider a case when there is a positive (lump sum) spillover s . In the *BASELINE* treatment $s = 0$, in the *SPILLOVER* treatment $s \in (\alpha, K)$.

2.2 Equilibrium Predictions

Proposition 1: If E_{M1} players choose action $M1$, E_{M2} players select action $M2$, and E_{M1+M2} players opt for action $M1 + M2$, there exist $\binom{N}{E_{M1}} \cdot \binom{N-E_{M1}}{E_{M2}} \cdot \binom{N-E_{M1}-E_{M2}}{E_{M1+M2}}$ pure strategy equilibria of the following form:

$$\left\{ \begin{array}{l} E_{M1} = \text{int} \left\{ c_{M1} - \frac{\alpha}{r_{M1} \cdot K} \right\} - E_{M1+M2} \\ E_{M2} = \text{int} \left\{ c_{M2} - \frac{\beta}{r_{M2} \cdot K} \right\} - E_{M1+M2} \\ E_{M1+M2} \leq \min \left\{ \text{int} \left\{ c_{M1} - \frac{\alpha-s}{r_{M1} \cdot K} \right\}, \text{int} \left\{ c_{M2} - \frac{\beta-s}{r_{M2} \cdot K} \right\} \right\} \end{array} \right\},$$

where $s = 0$ in the *BASELINE* treatment and $s \in (\alpha, K)$ in the *SPILLOVER* treatment. The proof of Proposition 1 is provided in Appendix A.

Proposition 2: There also exists a mixed strategy equilibrium, where each player takes action $M1$ with probability p_{M1} ; action $M2$ - with probability p_{M2} ; action $M1 + M2$ - with probability p_{M1+M2} ; and action *OUT* - with probability $p_{OUT} = 1 - p_{M1} - p_{M2} - p_{M1+M2}$. This equilibrium has the following form:

$$\left\{ \begin{array}{l} p_{M1} = 0 \\ p_{M2} = \max \left\{ \frac{c_{M2} - c_{M1} + \frac{\alpha-s}{r_{M1} \cdot K} - \frac{\beta}{r_{M2} \cdot K}}{N}, 0 \right\} \\ p_{M1+M2} = \min \left\{ \frac{c_{M1} - \frac{\alpha-s}{r_{M1} \cdot K}}{N}, \frac{s - \alpha - \beta + K \cdot (r_{M1} \cdot c_{M1} + r_{M2} \cdot c_{M2})}{K \cdot N \cdot (r_{M1} + r_{M2})}, 1 \right\} \end{array} \right\},$$

where $s = 0$ in the *BASELINE* treatment and $s \in (\alpha, K)$ in the *SPILLOVER* treatment. The proof of Proposition 2 is provided in Appendix A.

2.3 Experimental Implementation

We conducted eight sessions of the experiment in the laboratory of the Institute for Entrepreneurial Studies and Innovation Management at the Humboldt-Universität zu Berlin.

Fourteen participants took part in each session, yielding a total of 112 participants in the experiment.³ All participants were recruited through the Institute's online invitation system.

The majority of participants were students at the Humboldt-Universität zu Berlin. More than 56% of them studied either Economics or Business Administration. The average age was 28 years with a median of 27 and a standard deviation of 4.9. In terms of gender composition, 41% of participants were female and 59% - male. The majority of participants had some experience with economic experiments. However, none of them have taken part in experiments on MEG before.

The experiment was conducted using the experimental software z-Tree (Fischbacher, 2007). Upon arriving at the laboratory, each participant was seated at a workspace, equipped with a personal computer, scratch paper and a pen. A calculator was built in all decision screens. The workspace of each participant was separate and could not be seen by his or her counterparts or the experimenter. The session was monitored and any communication between participants was strictly forbidden.

All participants received two experimental tasks. In the first task, we measured their attitudes towards risk using the Holt and Laury (2002) procedure. In the second task, participants played an iterated TMEG. In one half of the sessions, participants played the *BASELINE* treatment of the game and the other half – the *SPILLOVER* treatment.

Participants received hard copies of the experimental instructions for each experimental task separately (sample experimental instructions are provided in Appendix B). Instructions were read aloud by the experimenter. After that, participants had an opportunity to re-read the instructions and ask individual questions, which were answered in private.

During the TMEG, several conditions were held constant. Specifically, the number of players in every period was $N = 14$. Each period's initial endowment was $K = €3.00$.⁴ In order to enter Market 1 a player had to pay $\alpha = €0.60$. The cost of entry into Market 2 was $\beta = €0.06$. Positive multiplier for Market 1 was $r_{M1} = 3$. The multiplier for Market 2 was $r_{M2} = 1$. In the *SPILLOVER* treatment of the TMEG, the amount of spillover s was equal to €1.50.

We have constructed four combinations of the market capacities:

- Combination 2-12: $c_{M1} = 2$ and $c_{M2} = 12$;
- Combination 4-10: $c_{M1} = 4$ and $c_{M2} = 10$;
- Combination 6-8: $c_{M1} = 6$ and $c_{M2} = 8$;
- Combination 7-7: $c_{M1} = 7$ and $c_{M2} = 7$.

³ In the experiment, the group size for the TMEG was fourteen participants per session because the experimental laboratory at the Humboldt-Universität zu Berlin had a space limitation of fourteen places.

⁴ At the time of the experiment the exchange rate was $€1 = \$1.41$.

In both treatments, all participants played twelve consecutive periods of each combination of the market capacities, yielding a total of 48 periods per session. However, to control for the possible order effects, we varied the order of combinations across sessions. Figure 1 presents four sequences of combinations, used in the second experimental task.

[INSERT Figure 1 HERE]

To simplify the task, each participant received supplementary tables along with the experimental instructions (sample tables are provided in Appendix B). Each table contained possible profit contingent on the selected individual strategy and the number of entrants into each market.⁵

To insure that participants understood the instructions and knew how to use the supplementary tables, they had to answer trial questions in the beginning of the second experimental task. In order to answer a question, participants had to type a numerical answer into a field on the computer screen (i.e. questions were not multiple choice). Participants were not able to proceed to the second experimental task until they answered all questions correctly. Combination of market capacities, used in the trial questions, did not repeat any of the combinations used in the second experimental task.

Similarly to the Camerer and Lovo (1999) experimental design, in the beginning of the TMEG, participants were asked to indicate their expectations about the number of entrants (excluding themselves) into Market 1 and Market 2. On the same screen, they were offered a choice among the four available actions from the action space $A \in \{M1, M2, M1 + M2, OUT\}$. They received feedback on the number of actual entrants into each market as well as on their individual payoff at the end of every period. After 48 periods of TMEG, payoffs from two randomly drawn periods were paid out. To avoid wealth effects across experimental tasks, the payoff from the first experimental task (risk attitudes elicitation procedure) was also determined at the end of the experiment. The experiment lasted approximately 1 hour. Average/median earnings of the participants were €14 with a standard deviation of €6.

3. Results

Similarly to the previous literature on MEG, we assess the data at two levels. First, we explore whether groups coordinate on the pure strategy Nash equilibria and check whether treatment variables influence behavior at the group level. Second, we analyze data at the individual level. We conduct representative agent analysis to determine whether the behavior of the representative agent can be rationalized by the mixed strategy Nash equilibrium. After that, we

⁵ Since any payoff lower than $K = €3.00$ was suboptimal, to insure that participants avoid making losses during the experiment, all negative values in the payoff function were substituted by zeros in the supplementary tables.

identify factors that determine the individual choice of a certain action using econometric analysis that takes into account the unobserved heterogeneity of participants.

3.1 Group Level

We have conducted a set of Kruskal-Wallis tests (Kruskal and Wallis, 1952) to compare frequencies of choosing each of the available actions across all eight groups of participants. We cannot reject the null hypothesis of no differences among the groups. Furthermore, there are no statistically significant differences across groups between the *BASELINE* and the *SPILLOVER* treatment.⁶ This allows us to pool the data from all sessions of the experiment to conduct our analysis.

3.1.1 Coordination

Experimental results reveal that in both treatments participants fail to coordinate on the pure strategy Nash equilibria at a group level. Columns two through five in Table 1 and Table 2 provide numerical solutions for the Nash equilibria in pure strategies for all combinations of market capacities, used in the second experimental task.⁷ Column six in Table 1 and Table 2 depicts a fraction of periods across all groups in the *BASELINE* and the *SPILLOVER* treatment respectively, when participants have coordinated on each of the pure strategy equilibria.

Similarly to Rapoport et al. (2000), we have conducted a simulation with 100 groups of computer-generated agents in addition to the laboratory TMEG. We did so in order to compare observed behavior with the behavior of agents, who play according to the predictions of the mixed strategy equilibrium. All 1,400 agents have been programmed to play mixed strategy Nash equilibria (Table 3 provides numerical solutions for the equilibria in mixed strategies for each combination of the market capacities in the *BASELINE* and the *SPILLOVER* treatment). Results of this simulation are presented in the seventh column of Table 1 and Table 2.⁸

[INSERT Table 1, Table 2, and Table 3 HERE]

The cases of pure strategy equilibrium play across groups in both treatments are very rare (see Table 1 and Table 2). Particularly, in the *BASELINE* treatment, participants coordinate on pure strategy Nash equilibria 6 out of 48 periods (12.5%), 5 out of 48 periods (10.5%), 5 out of 48 periods (10.5%) and never out of 48 (0%) in combinations 2-12, 4-10, 6-8 and 7-7 respectively

⁶ Statistical tests were conducted using the Stata/SE 10.0 software. Detailed test results with significance levels are available from the authors upon request.

⁷ Numerical solutions for Nash equilibria in pure and mixed strategies were calculated using the MatLab 7.4 package. Program files are available from the authors upon request.

⁸ Note that in both treatments mixed strategy equilibrium requires that the probability of entering Market 1 is equal to zero ($p_{M1} = 0$). Therefore, in the simulation with computer-generated agents, the outcome of the game never coincides with a pure strategy Nash equilibrium, where $E_{M1} > 0$.

across all four groups. In the *SPILLOVER* treatment, there is only one case (2.1%) of the pure strategy equilibrium play in 2-12 combination.

Moreover, in contrast to previous studies on MEG (e.g. Roth and Erev, 1995, Erev and Rapoport, 1996), groups do not seem to converge to the Nash equilibrium as they progress. Particularly, in the *BASELINE* treatment, Group 1 has coordinated on the Nash equilibria in periods 10, 17, 23 and 31; Group 2 – in periods 16, 24, 39 and 41; Group 3 – in periods 12, 16 and 47; and Group 4 – in periods 10, 31, 41 and 47. In the *SPILLOVER* treatment, three groups have never coordinated on any of Nash equilibria in pure strategies and one group has played according to the equilibrium prediction in period 30. This observation, however, may be due to the fact that groups have played twelve periods of each combination, which may or may not be enough to observe convergence given the complexity of the decision task.

Nevertheless, our finding that groups do not seem to converge to pure strategy equilibrium solutions in the iterated play is consistent with results from recent studies on route choice behavior (Selten et al., 2004) and the Braess Paradox (Rapoport et al., 2008). In a similar setting to the MEG, these studies show that with experience players tend to choose Pareto-deficient equilibria, even at a cost of decline in their earnings (e.g. Rapoport et al., 2008). Therefore, this paper contributes to the literature, documenting that even if a pure strategy equilibrium is reached by chance, there appear to be forces of sequential dynamics that divert players from coordinating on this equilibrium repeatedly in the iterated play.

Interestingly, in the *BASELINE* treatment, experimental participants seem to coordinate better than the computer-generated agents in the combinations 2-12, 4-10 and 6-8. However, the simulated fractions of the pure strategy play were higher than observed fractions in the *SPILLOVER* treatment and combination 7-7 of the *BASELINE* treatment. Since both experimental participants and computer-generated agents exhibit low coordination levels, the overall comparison between the observed and simulated outcomes suggests that observed behavior might be explained by the mixed strategy equilibrium prediction.

3.1.2 Degree of Overentry and Market Capacity

In the previous subsection we have established that groups in the experiment do not appear to play according to the predictions of the Nash equilibria in pure strategies. In this subsection we explore *how* the groups deviate from the equilibrium prediction. In particular, we investigate whether groups exhibit over- or underentry into each of the markets and identify factors that precipitate such behavior.

Recall from the experimental design (see Section 2) that there is a positive cost of entry associated with each market. Therefore, entrants into Market i ($i \in \{1,2\}$) receive a positive payoff ($\pi > K$) only if $E_{Mi} \leq \theta_{Mi}$, where θ_{Mi} is the cut-off entry value for Market i and $\theta_{Mi} = c_{Mi} - 1$. A group overenters into Market i if $E_{Mi} > \theta_{Mi}$, underenters into Market i if $E_{Mi} < \theta_{Mi}$ and enters exactly to the cut-off value of Market i if $E_{Mi} = \theta_{Mi}$. Based on this

definition of over- and underentry, Table 4 provides the number (percentage) of periods when groups exhibited overentry ($E_{Mi} > \theta_{Mi}$), underentry ($E_{Mi} < \theta_{Mi}$) and when the level of entry was equal to the cut-off value ($E_{Mi} = \theta_{Mi}$) for Market 1 and Market 2 separately. Table 4 suggests that groups tend to exhibit overentry in the majority of rounds.

[INSERT Table 4 HERE]

In order to establish the impact of treatment variables on the group outcome of the game in each round, we have used logit regression analysis. The probability that group $g \in \{1,8\}$ will have an entry outcome e is given by:

$$p_g^e = \frac{\exp\{\beta_1 X1_g^e + \beta_2 X2_g^e + \beta_3 X3_g^e + \beta_4 X4_g^e\}}{1 + \exp\{\beta_1 X1_g^e + \beta_2 X2_g^e + \beta_3 X3_g^e + \beta_4 X4_g^e\}}$$

Explanatory variables $X1, \dots, X4$ are described in Table 5 and regression coefficients β_1, \dots, β_4 are estimated by maximizing the log-likelihood function

$$L = \sum_{ge} I_{ge} \cdot \ln p_g^e + (1 - I_{ge}) \cdot \ln(1 - p_g^e),$$

where $I_{ge} = 1$ if a group overentered into a market, and $I_{ge} = 0$ if a group underentered into a market. The results of the logit regression are presented in Table 5.

[INSERT Table 5 HERE]

Results of the econometric analysis suggest that the combination of market capacities dummy ($X1$) is the only statistically significant explanatory variable. The estimation shows that there is an inverse relationship between the capacity of Market 1 and the overentry, i.e. the lower the capacity of the Market 1, the more likely groups are to overenter into Market 1. However, there is a direct relationship between the capacity of Market 2 and the overentry, i.e. the higher the capacity of the Market 2, the more likely groups are to overenter into Market 2.

There appear to be no order effects and no statistically significant differences between two experimental treatments. The sequence dummy ($X2$), order effect dummy ($X3$) and treatment dummy ($X4$) are not statistically significant.⁹

⁹ Since each group plays 48 periods of the game and receives feedback about income in each period, we have also conducted a random intercept logistic regression (e.g. Wooldridge, 2002) with over-/underentry into Market i as a binary outcome variable. The results of the panel analysis are the same as the results of the simple logit regression. This confirms the results of the non-parametric tests that there are no statistically significant differences in behavior at a group level.

3.2 Individual Level

3.2.1 Mixed Strategy Nash Equilibrium

While at a group level we observe coordination failure, individual data suggest that, on average, the behavior of participants in the experiment is very close to the mixed strategy Nash equilibrium prediction. Table 6 and Table 7 show predicted, observed and simulated fractions of rounds expected, played and simulated according to the mixed strategy Nash equilibrium in the *BASELINE* and the *SPILLOVER* treatment respectively.

[INSERT Table 6 and Table 7 HERE]

Since several predicted values are equal to zero, it is not possible to conduct a simple statistical test to see whether the predicted and observed values are different. The results of a set of the binomial tests, performed on all pairs of values, where the predicted value is positive, suggest that in the *BASELINE* treatment, in combination 7-7, participants on average try to play action *M2* (enter Market 2 and stay out of Market 1) more often than predicted ($p = 0.0007$). Even though in combination 7-7 participants, on average, decided to enter both markets simultaneously fewer times than expected, the difference between predicted/simulated and observed fractions was only marginally significant ($p = 0.0569$ and $p = 0.0506$ in the *BASELINE* and the *SPILLOVER* treatment respectively).

Previous results from the economics literature (e.g. Rapoport, 1995; Sundali et al., 1995; Rapoport et al., 1998; and etc.) show that the behavior of the representative agent in the MEG games appears to be very close to the predictions of the mixed strategy equilibrium. We find that even when the decision problem is sufficiently complex and the markets are heterogeneous in their costs and positive multipliers, this result is very robust.

3.2.2 Determinants of the Individual Action Choice and Unobserved Heterogeneity

Although the predictions of the mixed strategy equilibrium seem to explain behavior at the representative agent level, mixed strategy equilibrium fails to account for the individual differences among the experimental participants. Figure 2 and Figure 3 plot the number of periods (frequency) versus the number of experimental participants who have played each of the available actions from the action space *A*. It is apparent that individual profiles fail to support the mixed strategy equilibrium prediction. This finding is in line with the results from the previous economic experiments on MEG (e.g. Rapoport et al., 1998; Seale and Rapoport, 2000; and etc.).

[INSERT Figure 2 and Figure 3 HERE]

In this subsection we try to identify the determinants of the individual action choice using the econometric analysis that accounts for the unobserved heterogeneity among the

participants. We use a random intercept multinomial logit estimation (e.g. Haan and Uhlendorff, 2006) to investigate factors which influence participants' decisions to opt for a certain action. The probability that a participant i ($i \in [1,112]$) chooses action j ($j \in [0,3]$ where $0 = OUT$; $1 = M1$; $2 = M2$; $3 = M1 + M2$) in period t ($t \in [1,48]$) is given by

$$P(j|X1_{it} \dots XN_{it}, \alpha_i) = \frac{\exp(X1_{it}\beta_{1j} + X2_{it}\beta_{2j} + \dots + XN_{it}\beta_{Nj} + \alpha_{ij})}{\sum_{k=0}^3 \exp(X1_{it}\beta_{1k} + X2_{it}\beta_{2k} + \dots + XN_{it}\beta_{Nk} + \alpha_{ik})}$$

where $X1_{it}, \dots, XN_{it}$ are observed explanatory variables, that vary among individuals and over time, α_{ij} – unobserved individual effects and $\beta_{1j}, \dots, \beta_{Nj}$ – regression coefficients. The log-likelihood function of the multinomial logit with random intercepts has the following form:

$$LL = \prod_{i=1}^{112} \int_{-\infty}^{+\infty} \prod_{t=1}^{48} \prod_{j=0}^3 \left(\frac{\exp(X1_{it}\beta_{1j} + X2_{it}\beta_{2j} + \dots + XN_{it}\beta_{Nj} + \alpha_j)}{\sum_{k=0}^3 \exp(X1_{it}\beta_{1k} + X2_{it}\beta_{2k} + \dots + XN_{it}\beta_{Nk} + \alpha_k)} \right)^{d_{ijt}} f(\alpha) d\alpha$$

where $d_{ijt} = 1$ if individual i chooses alternative j at time t and $d_{ijt} = 0$ otherwise. Action $0 = OUT$ is taken as a base category for the model estimation.¹⁰ Unobserved heterogeneity α_{ij} is assumed to be independent of the explanatory variables $X1_{it}, \dots, XN_{it}$. The integral in the log-likelihood function is approximated using the adaptive quadrature method (Rabe-Hesketh et al., 2002).¹¹

Since experimental participants face markets with different capacities and state their expectations about the number of entrants into Market 1 and Market 2, some of the heterogeneity may originate in the combination of market capacities or in participants' expectations of over- or underentry. In order to control for different sources of heterogeneity, in addition to the basic two-level random intercept multiple logit regression, described above, we use two other models (a three-level random intercept multiple logit regression and a four-level random intercept multiple logit regression). In the three-level model, apart from the random intercept at the individual participant level (level 2), we use a random intercept at the level of combination of market capacities (level 3). In the four-level model, in addition to the random intercept at the individual participant level (level 2), we have constructed a binary expectation variable for each market. This variable is equal to 1 if a participant expects overentry into a market and to 0 otherwise. We use random intercepts at level 3 (expectation of over- or underentry into Market 1) and at level 4 (expectation of over- or underentry into Market 2). Table 8 provides the results of the estimated models.

¹⁰ We have also conducted estimations with $1 = M1$, $2 = M2$ and $3 = M1 + M2$ as base categories. The results appear to be very robust irrespective of the choice of the base variable.

¹¹ We have also approximated the log-likelihood function using Gauss-Hermite quadrature, however, the fit of adaptive quadrature was always superior (i.e. log-likelihood function obtained by the estimation with the adaptive quadrature approximation was always greater than that of the estimation approximated via Gauss-Hermite method).

[INSERT Table 8 HERE]

We consider fifteen explanatory variables. As suggested in the literature (e.g. Camerer and Lovo, 1999), in a MEG players should take into account their expectations about the number of entrants into a market. Variables $X1_{it}$ (adjusted expected entrants into Market 1) and $X2_{it}$ (adjusted expected entrants into Market 2) capture the participants' self-reported expectations of the number of their counterparts who will enter Market 1 and Market 2 respectively. Since markets have different capacities, these self-reported values are divided by the cut-off values θ_i for each market.

Participants receive feedback after each period. Therefore, a low or zero payoff and/or an observed excess entry into a market may have an impact on the next period's choice of an action. Variable $X3_{it}$ is equal to zero if a participant's payoff in the previous period was less than K and to one otherwise. Binary dummies $X4_{it}$ and $X5_{it}$ are equal to one if a group has exhibited overentry into Market 1 and Market 2 correspondingly, and are equal to zero otherwise.

Six explanatory variables reflect the personal characteristics of the experimental participants. Variables $X6_{it}$ and $X7_{it}$ capture, respectively, the self-reported gender and age of the participants. Camerer and Lovo (1999) and Bolger et al. (2008) find that overconfidence has an impact on entry decisions. Although it is not the purpose of our analysis to explore the impact of individual or relative confidence on entry decisions, we construct two indicators of overconfidence. $X8_{it}$ depicts the self-reported level of participant's confidence in his or her ability to take a simple IQ test compared with other participants in the experiment. $X9_{it}$ is a self-reported measure of participants' performance in the IQ test in comparison with co-workers or students in their study group.

All participants are ranked according to their answers to the Machiavelli V scale (Christie and Gies, 1970). The lower the rank (variable $X10_{it}$), the more likely an individual is to behave according to the Machiavelli principles. This rank can be used as a proxy for social preferences (the lower the rank, the more an individual is self-oriented and less socially preferring).

Recall from the description of the experiment (see Section 2) that in the first experimental task, all participants are subjected to the risk attitude elicitation procedure (Holt and Laury, 2002). During this procedure, participants have to make ten consecutive choices between a relatively risky and a relatively safe lottery. The probabilities for the different outcomes of the lotteries are systematically varied from 0.1 to 1. The number of safe choices (i.e. choosing a relatively safe lottery over a relatively risky lottery) is used as an indicator of participant's risk attitude (risk attitude rank). Variable $X11_{it}$ captures the risk attitude rank of the participants, elicited during the first experimental task (see Table 9). The lower the rank, the more an individual is risk seeking.

[INSERT Table 9 HERE]

In terms of their risk attitudes, more than half of participants (61.6%) are at least slightly risk averse (see Table 9). The average risk attitude rank was 5.26 (slightly risk averse) with a median rank of 5.00 (slightly risk averse) and a standard deviation of 1.52. Six participants made inconsistent choices and could not be classified in terms of risk attitudes.¹² The results of the Mann-Whitney-Wilcoxon two sample rank-sum test (Wilcoxon, 1945 and Mann and Whitney, 1947) show that there are no statistically significant differences between risk attitudes of participants in the *BASELINE* treatment and the *SPILLOVER* treatment ($p = 0.8640$).

Four explanatory variables in the estimation capture various treatment effects. Particularly, $X12_{it}$ depicts the impact of the *BASELINE* ($X12_{it} = 0$) and the *SPILLOVER* ($X12_{it} = 1$) treatment. Sequence ($X13_{it}$) and combination ($X14_{it}$) dummies account for the influence of four different sequences (see Figure 1) and four combinations of the market capacities (2-12, 4-10, 6-8, 7-7) used in the experiment. Finally, the order effect variable $X15_{it}$ stands for the time period (from 1 to 48).

We find that results obtained by estimating three models with different sources of heterogeneity are remarkably similar. Four-level model ($LL = -4765.4171$) appears to fit the data better than the other two models, though two-level model ($LL = -4850.4228$) performs slightly better than the three-level model ($LL = -4870.7311$).

We find that four explanatory variables are statistically significant when participants make decisions to take action *M1* in all three estimated models: adjusted expected entrants into Market 1 ($X1_{it}$), payoff dummy ($X3_{it}$), impact of previous overentry into Market 2 ($X5_{it}$), and combination dummy ($X14_{it}$). The fewer counterparts a participant expects to enter Market 1, the more likely he or she is to opt for action *M1* as opposed to the non-entry action (*OUT*). This result may have two possible interpretations. First, participants who play action *M1* take into account the expected number of entrants and enter when this number is below the market capacity. Second, this result may also suggest that participants who play action *M1* systematically underestimate the number of entrants into Market 1.

The lower the capacity of Market 1, the more likely participants are to choose action *M1*. This could be explained by the fact that the potential payoff from entering Market 1 when it is relatively small (if there is no overentry) is lower than the potential payoff from entering Market 1 when it is relatively large (see supplementary tables in Appendix B). Therefore, participants may anticipate relatively low competition on Market 1 when it is relatively small, which precipitates frequent entry.

If a participant has experienced a loss in the previous period (i.e. his or her profit has been lower than the initial endowment), a participant is more likely to play action *M1*. This finding may suggest that participants tend to choose an entry action with relatively high potential

¹² In our estimation, participants with inconsistent choices have been assigned a median rank (5).

payoff (if there is no overentry), versus staying out action (*OUT*), to compensate for the losses incurred in the previous period.

Interestingly, if a participant does not observe overentry into Market 2 in the previous period, he or she is more likely to enter Market 1. Moreover, the estimation of the two- and the three-level models suggests that the fewer entrants a participant expects on Market 2, the more likely he or she is to enter Market 1 (variable $X_{2_{it}}$). These two results might seem counter-intuitive. However, even though only one of our self-reported measures of overconfidence (variable $X_{9_{it}}$) turned out to be statistically significant in the three-level model, one possible explanation may be that statistically significant variables $X_{1_{it}}$, $X_{2_{it}}$ and $X_{5_{it}}$ provide indirect evidence that experimental participants generally underestimate the number of entrants into both markets. Particularly compared to those who choose to stay out of any of the markets participants who enter Market 1 and stay out of Market 2 think that their counterparts do not have enough courage to enter any of the markets (including Market 2 with relatively large capacity and relatively low multiplier). Low entry into Market 2, observed in the previous period, provides participants with an additional reason to believe that their counterparts are unlikely to enter any of the markets and, therefore, will play action *OUT*.

Two explanatory variables are statistically significant for the choice of action *M2* in all three estimated models: adjusted expected entrants into Market 2 ($X_{2_{it}}$), and combination dummy ($X_{14_{it}}$). The fewer entrants expected on Market 2, the more likely a participant is to take action *M2*. The higher the capacity of Market 2, the more likely a participant is to choose action *M2*.

Similar to the results for the action *M1*, the two- and three-level models show that the fewer counterparts a participant expects to enter Market 1, the more likely he or she is to play action *M2* (variable $X_{1_{it}}$). This may also suggest that participants who choose to play any of the available entry strategies underestimate the number of entrants into both markets.

According to the two- and the four-level models, participants who receive payoff below their initial endowment are more likely to play action *M2* than action *OUT* (variable $X_{3_{it}}$). Even though variable $X_{3_{it}}$ for action *M2* is significant at a lower level than for action *M1*, this result suggests that participants try to counterbalance a loss experienced in the previous period by taking an entry action as opposed to the staying out action.

Finally, six factors appear to be statistically significant when participants opt for action *M1 + M2*: adjusted expected entrants into Market 1 ($X_{1_{it}}$), adjusted expected entrants into Market 2 ($X_{2_{it}}$), payoff dummy ($X_{3_{it}}$), impact of previous overentry into Market 1 ($X_{4_{it}}$), risk attitude rank dummy ($X_{11_{it}}$) and combination dummy ($X_{14_{it}}$). The fewer entrants a participant expects to enter Market 1 and Market 2, the more likely he or she is to opt for action *M1 + M2*. Loss observed in the previous period precipitates a higher chance of choosing action *M1 + M2*. If participants observe underentry into Market 1 (variable $X_{4_{it}}$) according to all three estimated

models and into both markets (variables $X4_{it}$ and $X5_{it}$) according to the two- and the four-level models, they are more likely to take action $M1 + M2$.

The lower the capacity of Market 1 and the higher the capacity of Market 2, the more likely participants are to enter into both markets simultaneously (variable $X14_{it}$). There are two possible explanations of this finding. First, participants try to indemnify potential loss on Market 1 with low capacity by also entering Market 2 with high capacity. By entering two markets simultaneously, they try to insure that their payoff will be greater than their initial endowment. Second, similarly to action $M1$, participants who play action $M1 + M2$ may be attracted to Market 1 when it is relatively small (due to the high potential payoff) and enter Market 1 and Market 2 simultaneously because of the relatively low cost of entry into Market 2.

We also find that risk attitude rank, obtained through the Holt and Laury (2002) procedure, has a statistically significant impact on entry decisions (variable $X11_{it}$). According to all three models, participants who play action $M1 + M2$ appear to be more risk seeking than those who opted for action OUT . According to the three- and the four-level models, the lower the risk attitude rank of a participant, the more likely he or she is to opt for action $M2$.

These results have two interesting implications. First, they indicate a possible link between risk attitude and market entry decisions, which has not been studied in the literature on MEG. Second, even though the risk that participants face in two experimental tasks is qualitatively different, these results seem to suggest that there might be some correlation between individual (non-strategic) risk faced by the experimental participants in the Holt and Laury (2002) procedure and interactive (strategic) risk in MEG. It is left to future research to explore this tentative hypothesis and investigate the relation between different kinds of risk.

When we account for the heterogeneity due to the combination of market capacities and entry expectations, participants with relatively low Machiavelli V scale rank (Christie and Gies, 1970) appear to be more likely to choose any of the entry actions in the three-level model or actions $M1$ and $M1 + M2$ in the four-level model (variable $X10_{it}$). Even though Machiavelli V scale rank is only a self-reported measure, this result may suggest a possible relation between social preferences and entry decisions.

Interestingly, reported personal characteristics do not seem to have a significant impact on individual decisions. The only exception is an effect of gender on entry decisions (variable $X6_{it}$) in the four-level model. We find that men are more likely to choose option $M1 + M2$ than women.

There is only one instance of treatment effect in our analysis (variable $X12_{it}$). In the three-level model, participants in the *SPILLOVER* treatment are more likely to enter both markets simultaneously compared to those in the *BASELINE* treatment.

Finally, the estimated variance of the random intercept at the individual participant level (level 2) is 2.2173, 3.3354 and 3.9609 in the two-, three- and four-level model respectively. This variance in all estimated models is much higher than the variance of the random intercepts at the combination level or level of expectations of over- and underentry into each market. This result suggests that there is substantial variability in the propensity to make an entry decision ($M1, M2, M1 + M2$) as opposed to the staying out decision (OUT) due to the unobserved individual heterogeneity of the experimental participants.

4. Discussion

This paper has considered an iterated TMEG with heterogeneous markets: an innovative market with low capacity, high entry cost and high potential payoff and less innovative market with high capacity, low entry cost and low potential payoff. Players have an opportunity to stay out of all available markets, choose one of the markets or enter both markets simultaneously.

Our results can be partitioned into two clusters: group results and individual results. At the group level we observe coordination failures. Groups tend to exhibit overentry into both markets. Moreover, this tendency to overenter has an interesting property. There is a statistically significant relation between the propensity of overentry and market capacity. The lower the capacity of the innovative market and the higher the capacity of the less innovative market, the higher the propensity to detect overentry into these respective markets. This result provides a powerful tool for forecasting overentry on real markets.

At an individual level, we find that the behavior of the representative agent is very close to the predictions of the mixed strategy equilibrium. However, this prediction fails to explain individual differences. By accounting for the unobserved heterogeneity, we find that a low number of expected entrants into the market as well as loss or underentry at the group level experienced in the previous period both have a significant impact on the individual action choice. This finding, together with the observation of overentry, may suggest that participants tend to underestimate the level of possible entry into each market. In other words, participants may underrate the number of entrants even though they do not self-select into the experiment based on their abilities as, for example, in the Camerer and Lovo (1999) experiment.

While the non-experimental studies on relationship between the new business failure and market capacity are rare due to the complexity of obtaining the data, our results may provide an explanation for the high rates of failure in the innovative industries (e.g. Tucker, 2002). Namely, new businesses are attracted to the high potential payoffs of the innovative markets. However, due to the complexity of the decision problem, they underestimate the level of entry and often drop out of the market at the early stages.

The finding that the effect of capacity size in the experiment moves in different directions for innovative and less innovative market offers an interesting hypothesis that the tendency to

underestimate entry may depend on the capacity and other characteristics of the market. Especially when the market is very attractive in terms of its potential payoff does a player's propensity of entry underestimation grow as the market capacity declines, i.e. the lower the market capacity, the more a player underestimates potential entry. Yet, when the market is not very attractive in terms of its potential payoff, a player's propensity of entry underestimation increases as the market capacity grows, i.e. the greater the market capacity, the more a player underestimates the potential entry.

This paper is the first attempt to incorporate unobserved heterogeneity into the analysis of market entry situations. It is left to future research to explore the extent to which the individual effects play a role in the market entry decisions using the non-experimental data from the field as well as economic experiments. Some possible extensions of this research in the experimental domain may include introducing heterogeneity into the entrant's payoff structure and constructing markets with stochastic or ambiguous capacities.

Tables and Figures

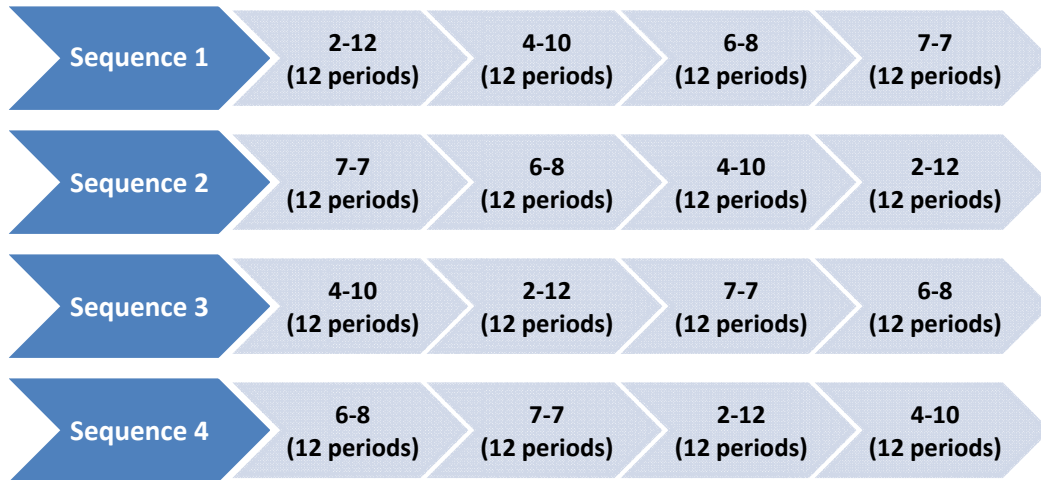


Figure 1 Sequences of Combinations in the Experiment

Table 1 Predicted and Observed Pure Strategy Nash Equilibria in the *BASELINE* Treatment

Combination	Nash Equilibrium in Pure Strategies				Observed % of periods (4 groups)	Simulated % of periods (100 groups)
	E_{M1}	E_{M2}	E_{M1+M2}	E_{OUT}		
2-12	0	10	1	3	8.3	5.5
	1	11	0	2	4.2	0.0
4-10	0	6	3	5	4.2	4.8
	1	7	2	4	-	-
	2	8	1	3	6.3	-
	3	9	0	2	-	-
6-8	0	2	5	7	-	0.3
	1	3	4	6	2.1	-
	2	4	3	5	2.1	-
	3	5	2	4	6.3	-
	4	6	1	3	-	-
	5	7	0	2	-	-
7-7	0	0	6	8	-	16.1
	2	2	4	6	-	-
	3	3	3	5	-	-
	4	4	2	4	-	-
	5	5	1	3	-	-
	6	6	0	2	-	-

Table 2 Predicted and Observed Pure Strategy Nash Equilibria in the SPILLOVER Treatment

Combination	Nash Equilibrium in Pure Strategies				observed % of periods (4 groups)	simulated % of periods (100 groups)
	E_{M1}	E_{M2}	E_{M1+M2}	E_{OUT}		
2-12	0	9	2	3	2.1	7.5
4-10	0	5	4	5	-	4.9
6-8	0	1	6	7	-	5.2
7-7	0	0	7	7	-	19.7

Table 3 Mixed Strategy Equilibria for BASELINE and SPILLOVER Treatments

Combination	BASELINE ($s = 0$)				SPILLOVER ($s = 1.5$)			
	p_{M1}	p_{M2}	p_{M1+M2}	p_{OUT}	p_{M1}	p_{M2}	p_{M1+M2}	p_{OUT}
2-12	0.0000	0.7176	0.1381	0.1443	0.0000	0.7057	0.1500	0.1443
4-10	0.0000	0.4319	0.2810	0.2871	0.0000	0.4200	0.2929	0.2871
6-8	0.0000	0.1462	0.4238	0.4300	0.0000	0.1343	0.4357	0.4300
7-7	0.0000	0.0033	0.4952	0.5015	0.0000	0.0000	0.5050	0.4950

Table 4 Observed Number (Percentage) of Periods when Groups Exhibited Over- and Underentry

	Combination	Market 1			Market 2		
		$E_{Mi} > \theta_{Mi}$	$E_{Mi} < \theta_{Mi}$	$E_{Mi} = \theta_{Mi}$	$E_{Mi} > \theta_{Mi}$	$E_{Mi} < \theta_{Mi}$	$E_{Mi} = \theta_{Mi}$
BASELINE	2-12	33 (69)	1 (2)	14 (29)	27 (56)	4 (8)	17 (35)
	4-10	30 (63)	8 (17)	10 (21)	28 (58)	5 (10)	15 (31)
	6-8	30 (63)	7 (15)	11 (23)	19 (40)	18 (38)	11 (23)
	7-7	27 (56)	10 (21)	11 (23)	22 (46)	15 (31)	11 (23)
SPILLOVER	2-12	35 (73)	1 (2)	12 (25)	32 (67)	2 (4)	14 (29)
	4-10	34 (71)	1 (2)	13 (27)	30 (63)	9 (19)	9 (19)
	6-8	33 (69)	7 (15)	8 (17)	24 (50)	14 (29)	10 (21)
	7-7	28 (58)	8 (17)	12 (25)	20 (42)	11 (23)	17 (35)
TOTAL	2-12	68 (71)	2 (2)	26 (27)	59 (61)	6 (6)	31 (32)
	4-10	64 (67)	9 (9)	23 (24)	58 (60)	14 (15)	24 (25)
	6-8	63 (66)	14 (15)	19 (20)	43 (45)	32 (33)	21 (22)
	7-7	55 (57)	18 (19)	23 (24)	42 (44)	26 (27)	28 (29)

Table 5 Results of the Logit Regression

Explanatory variable	Description	Regression coefficient (standard error)	
		Market 1	Market 2
Combination dummy (X1)	0 – combination 2-12; 1 – combination 4-10; 2 – combination 6-8; 3 – combination 7-7 ¹³	-0.6359*** (0.1719)	-0.5834*** (0.1345)
Sequence dummy (X2)	0 – sequence 1; 1 – sequence 2; 2 – sequence 3; 3 – sequence 4	-0.0594 (0.1553)	0.0829 (0.1241)
Order effect (X3)	Period dummy from 1 to 48	0.0187 (0.0127)	0.0004 (0.0100)
Treatment dummy (X4)	0- <i>BASELINE</i> , 1 – <i>SPILLOVER</i>	0.5381 (0.3482)	0.2011 (0.2780)
Intercept	Intercept	2.2974*** (0.5545)	1.7001*** (0.4484)
Pseudo R ²		0.0829	0.0673
Log-likelihood (L)		-112.0787	-154.4963
Number of observations		293	280

*** - significant at 0.001 level

¹³ Note that the higher is the combination dummy, the greater is the capacity of Market 1 and the lower is the capacity of Market 2.

Table 6 Predicted, Observed and Simulated Frequencies of Playing Each of the Available Strategies According to the Mixed Strategy Equilibrium (BASELINE)

Combination	2-12				4-10				6-8				7-7			
	M1	M2	M1+M2	OUT	M1	M2	M1+M2	OUT	M1	M2	M1+M2	OUT	M1	M2	M1+M2	OUT
Prediction	0.00	8.61	1.66	1.73	0.00	5.18	3.37	3.45	0.00	1.75	5.09	5.16	0.00	0.04	5.94	6.02
Observed average	0.66	8.70	1.32	1.32	1.61	6.23	2.16	2.00	2.41	3.29	2.84	3.46	2.86	2.41	3.11	3.63
Simulated average	0.00	8.63	1.66	1.71	0.00	5.18	3.30	3.52	0.00	1.76	5.08	5.16	0.00	0.05	5.82	6.13
Observed median	0.00	9.50	0.00	1.00	1.00	6.00	1.00	1.00	2.00	3.00	1.50	2.50	2.50	2.00	2.50	3.00
Simulated median	0.00	9.00	2.00	2.00	0.00	5.00	3.00	3.00	0.00	2.00	5.00	5.00	0.00	0.00	6.00	6.00
Observed SD	1.72	3.24	2.34	2.05	2.12	3.56	3.06	2.69	2.29	3.06	3.30	3.54	2.43	2.70	2.92	3.54
Simulated SD	0.00	1.57	1.18	1.26	0.00	1.71	1.54	1.59	0.00	1.26	1.71	1.72	0.00	0.21	1.72	1.72

Table 7 Predicted, Observed and Simulated Frequencies of Playing Each of the Available Strategies According to the Mixed Strategy Equilibrium (SPILLOVER)

Combination	2-12				4-10				6-8				7-7			
	M1	M2	M1+M2	OUT	M1	M2	M1+M2	OUT	M1	M2	M1+M2	OUT	M1	M2	M1+M2	OUT
Prediction	0.00	8.47	1.80	1.73	0.00	5.04	3.51	3.45	0.00	1.61	5.23	5.16	0.00	0.00	6.06	5.94
Observed average	0.46	8.07	1.95	1.52	1.20	5.68	2.80	2.32	2.07	2.86	3.52	3.55	2.43	2.00	3.57	4.00
Simulated average	0.00	8.50	1.81	1.69	0.00	5.07	3.50	3.43	0.00	1.62	5.20	5.18	0.00	0.00	6.08	5.92
Observed median	0.00	8.00	1.00	1.00	0.00	5.50	2.00	1.50	1.00	2.00	2.00	3.00	2.00	1.00	3.00	4.00
Simulated median	0.00	9.00	2.00	2.00	0.00	5.00	3.00	3.00	0.00	2.00	5.00	5.00	0.00	0.00	6.00	6.00
Observed SD	0.85	3.07	2.56	2.25	2.02	3.48	3.14	2.76	2.48	2.42	3.41	3.32	2.31	2.58	3.40	3.53
Simulated SD	0.00	1.66	1.26	1.25	0.00	1.76	1.61	1.61	0.00	1.17	1.70	1.73	0.00	0.00	1.75	1.75

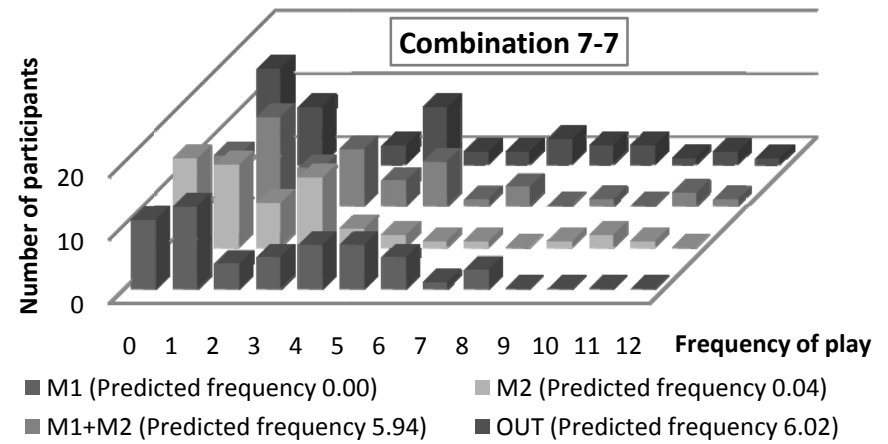
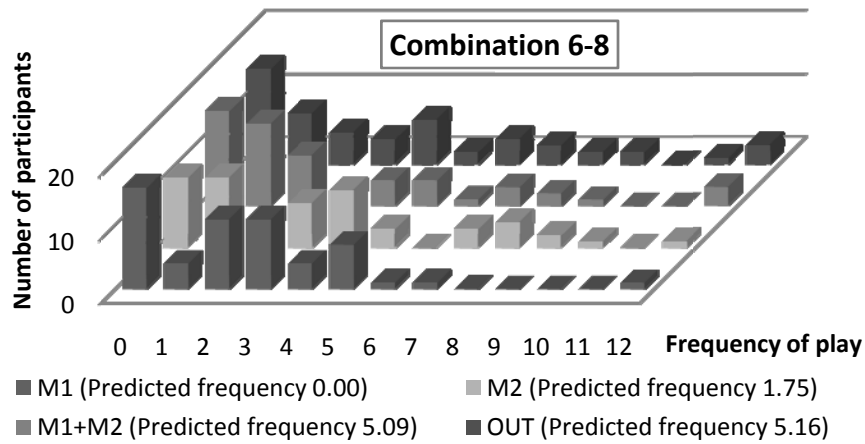
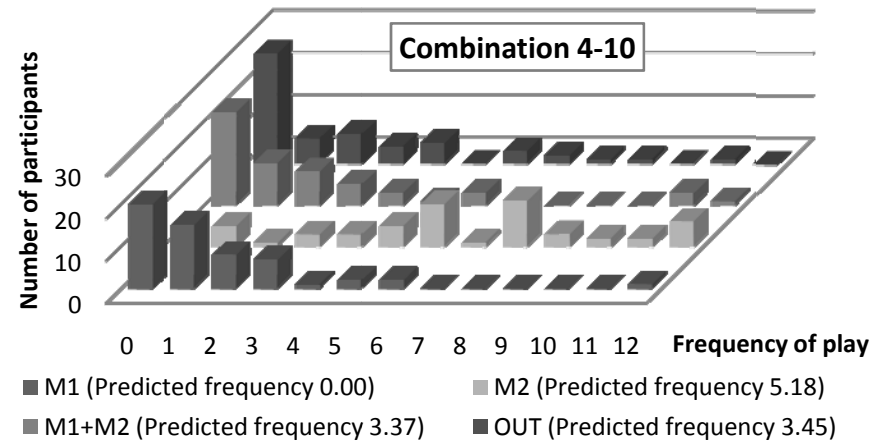
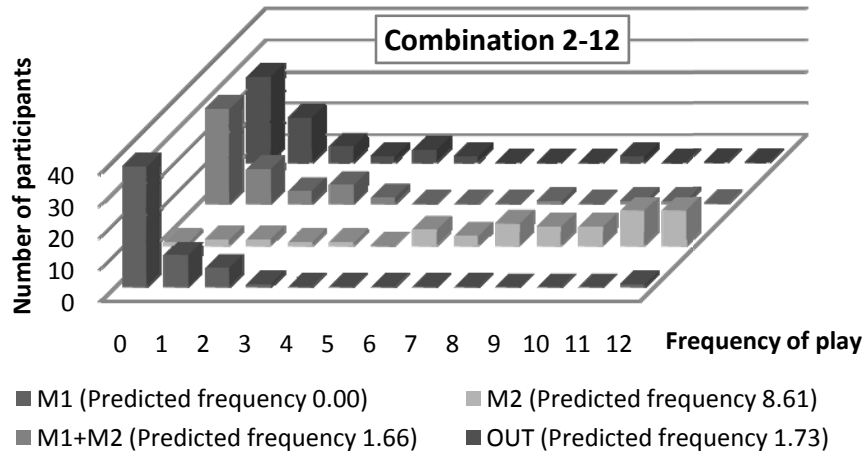


Figure 2 Observed Frequency of Playing Actions *M1*, *M2*, *M1+M2* and *OUT* among 56 participants in the *BASELINE* treatment

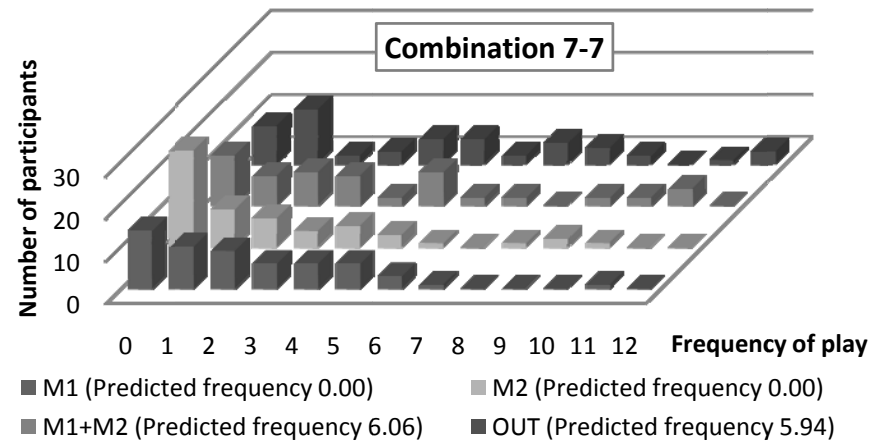
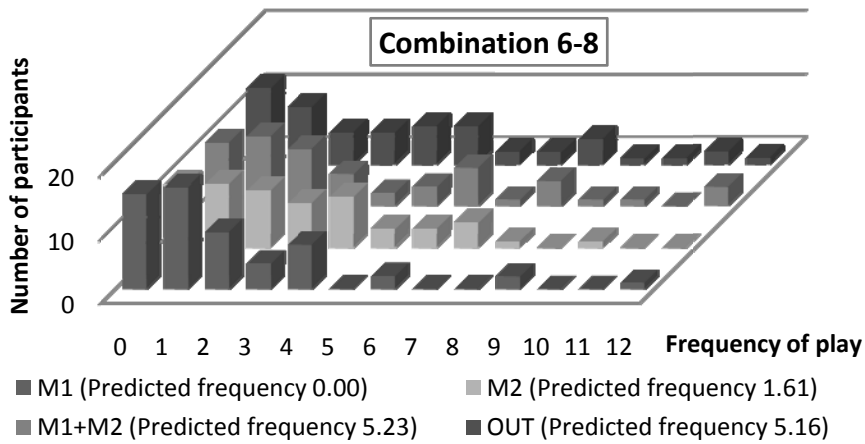
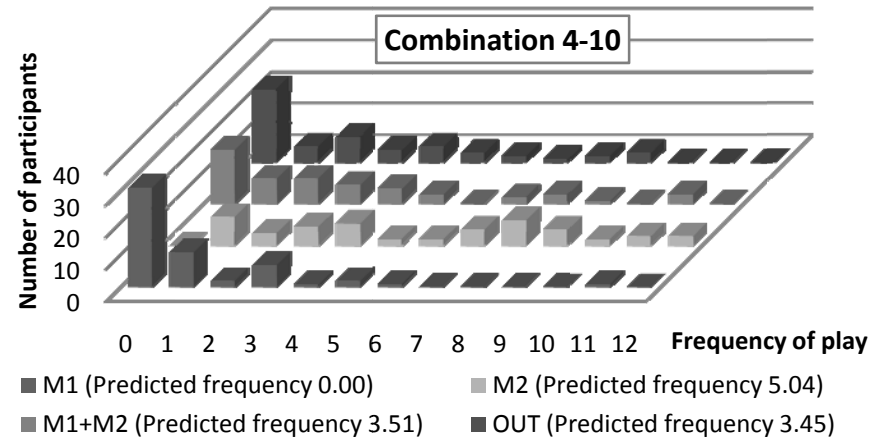
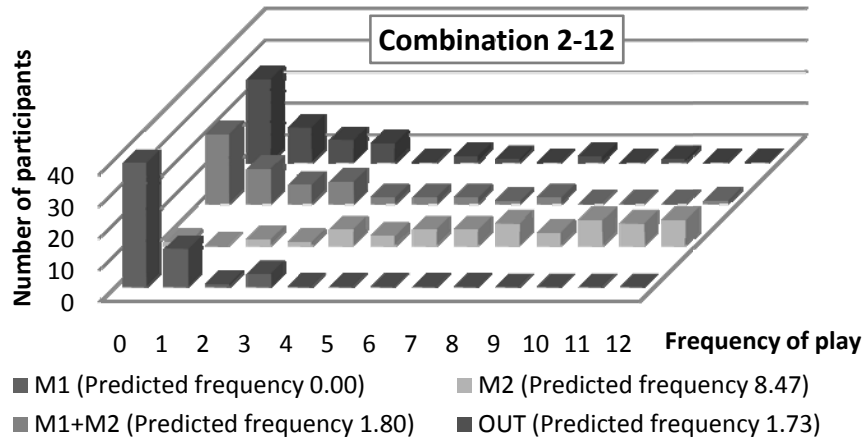


Figure 3 Observed Frequency of Playing Actions *M1*, *M2*, *M1+M2* and *OUT* among 56 participants in the *SPILLOVER* treatment

Table 8 Results of the Random Intercept Multinomial Logit Regression

Explanatory variable	Description	Marginal effect (standard error) <i>Two-Level Model</i>			Marginal effect (standard error) <i>Three-Level Model</i>			Marginal effect (standard error) <i>Four-Level Model</i>			
		Action <i>M1</i>	Action <i>M2</i>	Action <i>M1 + M2</i>	Action <i>M1</i>	Action <i>M2</i>	Action <i>M1 + M2</i>	Action <i>M1</i>	Action <i>M2</i>	Action <i>M1 + M2</i>	
		Adjusted expected entrants into Market 1 ($X1_{it}$)	Number of counterparts (from 0 to 13), who are expected to enter Market 1 divided by the cut-off value θ_1	-1.9864*** (0.1340)	-0.2162*** (0.0528)	-1.7209*** (0.1039)	-2.1316*** (0.1409)	-0.3319*** (0.0753)	-1.8792*** (0.1151)	-1.6262*** (0.1380)	-0.1172 (0.0604)
Adjusted expected entrants into Market 2 ($X2_{it}$)	Number of counterparts (from 0 to 13), who are expected to enter Market 2 divided by the cut-off value θ_2	-0.5792* (0.2952)	-4.8041*** (0.2823)	-4.4750*** (0.2893)	-1.0578*** (0.3184)	-5.1404*** (0.3036)	-4.8550*** (0.3109)	-0.0009 (0.4279)	-3.8663*** (0.4186)	-3.7051*** (0.4247)	
Payoff dummy ($X3_{it}$)	Payoff in the previous period (0 – if the payoff was lower than K and 1 otherwise)	-0.8355*** (0.1427)	-0.2704* (0.1183)	-0.7872*** (0.1322)	-0.6137*** (0.1516)	-0.0495 (0.1295)	-0.5517*** (0.1418)	-0.9672*** (0.1575)	-0.3845** (0.1318)	-0.8977*** (0.1456)	
Impact of previous overentry into Market 1 ($X4_{it}$)	0 – if $E_{M1} \leq \theta_1$ in the previous period, 1 – otherwise	-0.2020 (0.1352)	-0.1372 (0.1097)	-0.5309*** (0.1220)	-0.0926 (0.1417)	-0.0569 (0.1175)	-0.4309*** (0.1287)	-0.2321 (0.1487)	-0.1620 (0.1227)	-0.5548*** (0.1349)	
Impact of previous overentry into Market 2 ($X5_{it}$)	0 – if $E_{M2} \leq \theta_1$ in the previous period, 1 – otherwise	-0.5443*** (0.1256)	-0.1679 (0.1099)	-0.2547* (0.1176)	-0.5090*** (0.1315)	-0.1210 (0.1170)	-0.2069 (0.1237)	-0.5981*** (0.1392)	-0.2039 (0.1216)	-0.2965* (0.1299)	
Gender dummy ($X6_{it}$)	0 – male, 1 – female	-0.2741 (0.3333)	-0.04767 (0.3277)	-0.3948 (0.3305)	-0.1980 (0.2267)	0.0063 (0.2164)	-0.3294 (0.2218)	-0.4358 (0.2466)	-0.2463 (0.2390)	-0.5773* (0.2425)	
Age ($X7_{it}$)	Self-reported age	0.0248 (0.0340)	0.0028 (0.0337)	0.0161 (0.0338)	0.0277 (0.0232)	0.0040 (0.0225)	0.0191 (0.0228)	0.0449 (0.0245)	0.0232 (0.0240)	0.0370 (0.0242)	
Self-reported overconfidence measure 1 ($X8_{it}$)	Self-reported measure of participant's confidence in his/her ability to take a simple IQ test compared with other participants in the room (1 – place 1-3, 2 – place 4-6, 3 – place 7-9, 4 – place 10-12, 5 – place 13-14)	0.0849 (0.2036)	0.0737 (0.1998)	-0.0568 (0.2014)	0.1252 (0.1392)	0.1348 (0.1325)	-0.0028 (0.1353)	0.1080 (0.1489)	0.1314 (0.1435)	-0.0184 (0.1455)	
Self-reported overconfidence measure 2 ($X9_{it}$)	Self-reported measure of participant's confidence in his/her ability to take a simple IQ test compared with his/her co-workers/ other students in their study group (1 – place 1-3, 2 – place 4-6, 3 – place 7-9, 4 – place 10-12, 5 – place 13-14)	-0.2317 (0.1846)	-0.1351 (0.1816)	-0.1552 (0.1827)	-0.2802* (0.1247)	-0.1896 (0.1192)	-0.2019 (0.1213)	-0.2514 (0.1360)	-0.1738 (0.1316)	-0.1800 (0.1329)	
Machiavelli rank dummy ($X10_{it}$)	Individual rank based on the Machiavelli V scale. The lower is this rank; the more likely an individual is to behave according to the Machiavelli principles.	-0.0264 (0.0169)	-0.0157 (0.0166)	-0.0230 (0.0167)	-0.0374*** (0.0115)	-0.0246* (0.0111)	-0.0328** (0.0113)	-0.0331** (0.0126)	-0.0193 (0.0123)	-0.0286* (0.0124)	
Risk attitude rank dummy ($X11_{it}$)	A scale from 0 (risk seeking) to 10 (extremely risk averse), based on the number of safe choices made in the Holt and Laury (2002) risk attitude measure	0.0320 (0.1072)	-0.1067 (0.1052)	-0.2144* (0.1063)	-0.0219 (0.0738)	-0.1396* (0.0704)	-0.2637*** (0.0723)	-0.0275 (0.0797)	-0.1554* (0.0769)	-0.2747*** (0.0784)	
Treatment dummy ($X12_{it}$)	0 – BASELINE, 1 – SPILLOVER	-0.1982 (0.3223)	-0.1644 (0.3169)	0.3976 (0.3193)	-0.0623 (0.2196)	-0.0706 (0.2097)	0.5175* (0.2143)	-0.1791 (0.2371)	-0.1515 (0.2296)	0.4125 (0.2326)	
Sequence dummy ($X13_{it}$)	0 – sequence 1; 1 – sequence 2; 2 – sequence 3; 3 – sequence 4	-0.1052 (0.1422)	-0.0333 (0.1398)	-0.0320 (0.1408)	-0.1228 (0.0968)	-0.0487 (0.0926)	-0.0484 (0.0945)	-0.2200* (0.1062)	-0.1556 (0.1030)	-0.1482 (0.1043)	
Combination dummy ($X14_{it}$)	0 – combination 2-12; 1 – combination 4-10; 2 – combination 6-8; 3 – combination 7-7 ¹⁴	-0.4262*** (0.0649)	-0.8434*** (0.05477)	-0.5025*** (0.0594)	-0.5396*** (0.1269)	-0.9112*** (0.1214)	-0.5951*** (0.1239)	-0.4226*** (0.0722)	-0.8436*** (0.0623)	-0.4909*** (0.0668)	
Order effect ($X15_{it}$)	Period dummy from 1 to 48	0.0028 (0.0042)	0.0038 (0.0035)	0.0028 (0.0038)	0.0022 (0.0071)	0.0041 (0.0067)	0.0031 (0.0069)	0.0018 (0.0047)	0.0023 (0.0041)	0.0017 (0.0044)	
Intercept	Intercept	5.0504*** (1.2972)	8.8176*** (1.2724)	10.5484*** (1.2848)	6.2579*** (0.9878)	9.6367*** (0.9480)	11.5220*** (0.9680)	3.9712*** (1.0843)	7.5611*** (1.0501)	9.3472*** (1.0665)	
Log-likelihood (LL)		-4850.4228			-4870.7311			-4765.4171			
Variance, standard deviation and standard error for the random intercept (level 2)		2.2173	1.4890	0.2953	3.3354	1.8263	0.4045	3.9606	1.9901	0.5572	
Variance, standard deviation and standard error for the random intercept (level 3)		-			0.0268	0.1635	0.0036	0.6922	0.8320	0.1393	
Variance, standard deviation and standard error for the random intercept (level 4)		-			-			0.0001	0.0077	0.000014	
Number of level 1 units (Action); number of level 2 units (Individual)		4928	112		-			-			
Number of level 1 units (Action); number of level 2 units (Individual); number of level 3 units (Combination)		-			4928	112	4	-			
Number of level 1 units (Action); number of level 2 units (Individual); number of level 3 units (Expectation of under- or overentry on Market 1) and number of level 4 units (Expectation of under- or overentry on Market 2)		-			-			4928	112	2	2

* - significant at 0.05 level; ** - significant at 0.01 level; *** - significant at 0.001 level

¹⁴ Note that the higher is the combination dummy, the greater is the capacity of Market 1 and the lower is the capacity of Market 2.

Table 9 Risk Attitudes of Experimental Participants

Constant relative risk aversion (CRRA) characteristic			Number of participants (%)		
Risk attitude rank*	CRRA coefficient r	Description	<i>BASELINE</i>	<i>SPILLOVER</i>	TOTAL
2	$-0.95 < r \leq -0.49$	very risk seeking	1 (1.8)	1 (1.8)	2 (1.8)
3	$-0.49 < r \leq -0.15$	risk seeking	2 (3.6)	7 (12.5)	9 (8.0)
4	$-0.15 < r \leq 0.15$	risk neutral	14 (25.0)	12 (21.4)	26 (23.2)
5	$0.15 < r \leq 0.41$	slightly risk averse	12 (21.4)	10 (17.9)	22 (19.6)
6	$0.41 < r \leq 0.68$	risk averse	11 (19.6)	15 (26.8)	26 (23.2)
7	$0.68 < r \leq 0.97$	very risk averse	7 (12.5)	8 (14.3)	15 (13.4)
8	$0.97 < r \leq 1.37$	highly risk averse	1 (1.8)	2 (3.6)	3 (2.7)
9 or 10	$r > 1.37$	stay in bed	2 (3.6)	1 (1.8)	3 (2.7)
Mann-Whitney-Wilcoxon two-sample rank-sum statistics			$p=0.8640$		-
Average rank			5.32	5.21	5.26
Median rank			5.00	5.00	5.00
Standard deviation			1.53	1.52	1.52
Inconsistent¹⁵			6 (10.7)	0 (0.0)	6 (5.4)

* - Number of safe choices made in the Holt and Laury (2002) procedure

¹⁵ In the econometric analysis, inconsistent subjects were assigned the median rank (5).

References

- Bolger, F., Pulford, B. and A. Colman (2008) "Market Entry Decisions: Effects of Absolute and Relative Confidence," *Experimental Psychology*, 55(2), pp. 113-120.
- Camerer, C. (1990) "Behavioral Game Theory," in R. Hogarth, ed. *Insights in Decision Making: A tribute to Hillel J. Einhorn*, Chicago: University of Chicago Press.
- Camerer, C. and D. Lovo (1999) "Overconfidence and Excess Entry: An Experimental Approach," *The American Economic Review*, 89(1), pp. 306-318.
- Christie, R and F. Gies (1970) *Studies in Machiavellism*, Academic Press, New York.
- Dunne, T., Roberts, M. and L. Samuelson (1988) "Patterns of Firm Entry and Exit U.S. Manufacturing Industries," *Rand Journal of Economics*, 19(4), pp. 495-515.
- Erev, I. and A. Roth, (1998) "Predicting How People Play Games: Reinforcement Learning in Experimental Games with Unique, Mixed Strategy Equilibria," *American Economic Review*, 88(4), pp. 848-881.
- Erev, I. and A. Rapoport (1998) "Coordination, "Magic," and Reinforcement Learning in a Market Entry Game," *Games and Economic Behavior*, 23, pp. 146-175.
- Fischbacher, U. (2007) "z-Tree: Zurich Toolbox for Ready-made Economic Experiments," *Experimental Economics*, 10(2), pp. 171-178.
- Fischbacher, U. and Ch. Thöni (2008) "Excess Entry in an Experimental Winner-Take-All Market," *Journal of Economic Behavior and Organization*, 67, pp. 150-163.
- Haan, P. and A. Uhlendorff (2006) "Estimation of Multinomial Logit Models with Unobserved Heterogeneity Using Maximum Simulated Likelihood," *Stata Journal*, 6(2), pp. 229-245.
- Holt, Ch. and S. Laury (2002) "Risk Aversion and Incentive Effects," *American Economic Review*, 92(5), pp. 1644-1655.
- Grilli, L. and C. Rampichini (2005) "A Review of Random Effects Modelling Using GLLAMM in Stata," Working Paper, accessed at <http://www.cmm.bristol.ac.uk/learning-training/multilevel-m-software/reviewgllamm.pdf>
- Kahnman, D. (1988) "Experimental Economics: A Psychological Perspective" in R. Tietz, W. Albers, and R. Selten, eds. *Bounded Rational Behavior in Experimental Games and Markets*, New York: Springer-Verlag, pp. 11-18.
- Kruskal, W. and W. Wallis (1952) "Use of Ranks in One-criterion Variance Analysis," *Journal of the American Statistical Association*, 47, pp. 583-621.
- Mann, H. And D. Whitney (1947) "On a Test of Whether One of Two Random Variables Is Stochastically Larger Than the Other," *Annals of Mathematical Statistics*, 18, pp. 50-60.

- Rabe-Hesketh, S., Skrondal, A. and A. Pickles (2002) "Reliable Estimation of Generalised Linear Mixed Models Using Adaptive Quadrature," *Stata Journal*, 2(1), pp. 1-21.
- Rapoport, A. (1995) "Individual Strategies in a Market-Entry Game," *Group Decision and Negotiation*, 4(2), pp. 117-133.
- Rapoport, A., Seale, D. A., Erev, I. and J. A. Sundali (1998) "Equilibrium Play in Large Group Market Entry Games," *Management Science*, 44(1), pp. 129-141.
- Rapoport, A., Seale, D. and E. Winter (2000) "An Experimental Study of Coordination and Learning in Iterated Two-Market Entry Games," *Economic Theory*, 16, pp. 661-687.
- Rapoport, A., Seale, D. and E. Winter (2002) "Coordination and Learning Behavior in Large Groups with Asymmetric Players," *Games and Economic Behavior*, 39, pp. 111-136
- Rapoport, A., Kugler, T., Dugar, S. And E. Gisches (2008) "Choice of Routes in Congested Traffic Networks: Experimental Tests of the Braess Paradox," *Game and Economic Behavior*, in press
- Schelling, T. (1980) *The Strategy of Conflict*, Harvard University Press, Cambridge, MA.
- Seale, D. and A. Rapoport (2000) "Elicitation of Strategy Profiles in Large Group Coordination Games," *Experimental Economics*, 3, pp. 153-179.
- Selten, R. and W. Guth, (1982) "Equilibrium Point Selection in a Class of Market Entry Games," in M. Diestler, E. Furst, and G. Schwadlauer (eds.), *Games, Economic Dynamics, and Time Series Analysis*, Physica-Verlag, Wien-Wiirzburg, pp. 101-116.
- Selten, R., Schreckenberg, M., Chmura, T., Pitz, T., Kube, S., Hafstein, S., Chrobok, R., Pottmeier, A. and J. Wahle (2004), "Experimental Investigation of Day-to-Day Route Choice Behavior and Network Simulations of Autobahn-traffic in North Rhine Westphalia," in *Human Behavior and Traffic Networks*, Michael Schreckenberg and Reinhard Selten (eds.), Springer, Berlin., pp. 1-21.
- Sundali, J., Rapoport, A., and D. Seale (1995) "Coordination in Market Entry Games with Symmetric Players," *Organizational Behavior and Human Decision Processes*, 64(2), pp. 203-218.
- Tucker, R. (2002) *Driving Growth Through Innovation: How Leading Firms are Transforming Their Futures*, San Francisco, CA: Berrett-Koehler Publishing.
- Wilcoxon, F. (1945) "Individual Comparisons by Ranking Methods," *Biometrics Bulletin*, 1, pp. 80-83.
- Zwick, R. and A. Rapoport (2002) "Tacit Coordination in a Decentralized Market Entry Game with Fixed Capacity," *Experimental Economics*, 5, pp. 253-272.

Appendix A

Mathematical Appendix

Proof of Proposition 1:

If E_{M_1} players take action $M1$, E_{M_2} players choose action $M2$ and $E_{M_1+M_2}$ players opt for action $M1 + M2$, $\alpha > \beta$ and $r_{M_1} > r_{M_2}$, then equilibrium conditions are the following:

$$\begin{cases} E_{M_1} > 0 \\ E_{M_1} + E_{M_1+M_2} \leq c_{M_1} - \frac{\alpha}{r_{M_1} \cdot K} \\ K - \alpha + r_{M_1} \cdot K \cdot (c_{M_1} - E_{M_1} - E_{M_1+M_2}) \geq K - \beta + r_{M_2} \cdot K \cdot (c_{M_2} - E_{M_2} - E_{M_1+M_2} - 1) \\ K - \alpha + r_{M_1} \cdot K \cdot (c_{M_1} - E_{M_1} - E_{M_1+M_2}) \geq K - \alpha - \beta + r_{M_1} \cdot K \cdot (c_{M_1} - E_{M_1} - E_{M_1+M_2}) + r_{M_2} \cdot K \cdot (c_{M_2} - E_{M_2} - E_{M_1+M_2} - 1) + s \end{cases}$$

$$\begin{cases} E_{M_2} > 0 \\ E_{M_2} + E_{M_1+M_2} \leq c_{M_2} - \frac{\beta}{r_{M_2} \cdot K} \\ K - \beta + r_{M_2} \cdot K \cdot (c_{M_2} - E_{M_2} - E_{M_1+M_2}) \geq K - \alpha + r_{M_1} \cdot K \cdot (c_{M_1} - E_{M_1} - E_{M_1+M_2} - 1) \\ K - \beta + r_{M_2} \cdot K \cdot (c_{M_2} - E_{M_2} - E_{M_1+M_2}) \geq K - \alpha - \beta + r_{M_1} \cdot K \cdot (c_{M_1} - E_{M_1} - E_{M_1+M_2} - 1) + r_{M_2} \cdot K \cdot (c_{M_2} - E_{M_2} - E_{M_1+M_2}) + s \end{cases}$$

$$\begin{cases} E_{M_1+M_2} > 0 \\ -\alpha - \beta + r_{M_1} \cdot K \cdot (c_{M_1} - E_{M_1} - E_{M_1+M_2}) + r_{M_2} \cdot K \cdot (c_{M_2} - E_{M_2} - E_{M_1+M_2}) + s \geq 0 \\ K - \alpha - \beta + r_{M_1} \cdot K \cdot (c_{M_1} - E_{M_1} - E_{M_1+M_2}) + r_{M_2} \cdot K \cdot (c_{M_2} - E_{M_2} - E_{M_1+M_2}) + s \geq K - \alpha + r_{M_1} \cdot K \cdot (c_{M_1} - E_{M_1} - E_{M_1+M_2}) \\ K - \alpha - \beta + r_{M_1} \cdot K \cdot (c_{M_1} - E_{M_1} - E_{M_1+M_2}) + r_{M_2} \cdot K \cdot (c_{M_2} - E_{M_2} - E_{M_1+M_2}) + s \geq K - \beta + r_{M_2} \cdot K \cdot (c_{M_2} - E_{M_2} - E_{M_1+M_2}) \end{cases}$$

$$\begin{cases} N - E_{M_1} - E_{M_2} - E_{M_1+M_2} > 0 \\ K \geq K - \alpha + r_{M_1} \cdot K \cdot (c_{M_1} - E_{M_1} - E_{M_1+M_2} - 1) \\ K \geq K - \beta + r_{M_2} \cdot K \cdot (c_{M_2} - E_{M_2} - E_{M_1+M_2} - 1) \\ K \geq K - \alpha - \beta + r_{M_1} \cdot K \cdot (c_{M_1} - E_{M_1} - E_{M_1+M_2} - 1) + r_{M_2} \cdot K \cdot (c_{M_2} - E_{M_2} - E_{M_1+M_2} - 1) + s \end{cases}$$

Solving for E_{M_1} , E_{M_2} , and $E_{M_1+M_2}$ yields:

$$\begin{cases} E_{M_1} = \text{int} \left\{ c_{M_1} - \frac{\alpha}{r_{M_1} \cdot K} \right\} - E_{M_1+M_2} \\ E_{M_2} = \text{int} \left\{ c_{M_2} - \frac{\beta}{r_{M_2} \cdot K} \right\} - E_{M_1+M_2} \\ E_{M_1+M_2} \leq \min \left\{ \text{int} \left\{ c_{M_1} - \frac{\alpha-s}{r_{M_1} \cdot K} \right\}, \text{int} \left\{ c_{M_2} - \frac{\beta-s}{r_{M_2} \cdot K} \right\} \right\} \end{cases},$$

where $s = 0$ in the *BASELINE* treatment and $s \in (\alpha, K)$ in the *SPILLOVER* treatment. Given that there are N players, there are $\binom{N}{E_{M_1}} \cdot \binom{N-E_{M_1}}{E_{M_2}} \cdot \binom{N-E_{M_1}-E_{M_2}}{E_{M_1+M_2}}$ ways of selecting different combinations of E_{M_1} , E_{M_2} , and $E_{M_1+M_2}$ out of N .

Proof of Proposition 2:

Let each player select action $M1$ with probability p_{M_1} ; $M2$ - with probability p_{M_2} ; $M1 + M2$ - with probability $p_{M_1+M_2}$; and *OUT* - with probability $p_{OUT} = 1 - p_{M_1} - p_{M_2} - p_{M_1+M_2}$. The

probability that E_{M1} players choose action $M1$, E_{M2} take action $M2$ and E_{M1+M2} players opt for action $M1 + M2$ is

$$p(E_{M1}, E_{M2}, E_{M1+M2}) = (p_{M1})^{E_{M1}} \cdot (p_{M2})^{E_{M2}} \cdot (p_{M1+M2})^{E_{M1+M2}} \cdot (p_{OUT})^{E_{OUT}} \cdot \binom{N}{E_{M1}} \cdot \binom{N-E_{M1}}{E_{M2}} \cdot \binom{N-E_{M1}-E_{M2}}{E_{M1+M2}},$$

where $E_{OUT} = N - E_{M1} - E_{M2} - E_{M1+M2}$

Then equilibrium conditions could be specified as:

$$\begin{aligned} & \sum_{E_{M1}=0}^N \sum_{E_{M2}=0}^{N-E_{M1}} \sum_{E_{M1+M2}=0}^{N-E_{M1}-E_{M2}} [K - \alpha - \beta + r_{M1} \cdot K \cdot (c_{M1} - E_{M1} - E_{M1+M2}) + r_{M2} \cdot K \cdot \\ & \quad \cdot (c_{M2} - E_{M2} - E_{M1+M2})] \cdot p(E_{M1}, E_{M2}, E_{M1+M2}) = \\ & = \sum_{E_{M1}=0}^N \sum_{E_{M2}=0}^{N-E_{M1}} \sum_{E_{M1+M2}=0}^{N-E_{M1}-E_{M2}} [K - \alpha + r_{M1} \cdot K \cdot (c_{M1} - E_{M1} - E_{M1+M2})] \cdot p(E_{M1}, E_{M2}, E_{M1+M2}) = \\ & = \sum_{E_{M1}=0}^N \sum_{E_{M2}=0}^{N-E_{M1}} \sum_{E_{M1+M2}=0}^{N-E_{M1}-E_{M2}} [K - \beta + r_{M2} \cdot K \cdot (c_{M2} - E_{M2} - E_{M1+M2})] \cdot p(E_{M1}, E_{M2}, E_{M1+M2}) = \\ & = K. \end{aligned}$$

Solving for p_{M1} , p_{M2} , and p_{M1+M2} yields:

$$\begin{cases} p_{M1} = 0 \\ p_{M2} = \max \left\{ \frac{c_{M2} - c_{M1} + \frac{\alpha - s}{r_{M1} \cdot K} - \frac{\beta}{r_{M2} \cdot K}}{N}, 0 \right\} \\ p_{M1+M2} = \min \left\{ \frac{c_{M1} - \frac{\alpha - s}{r_{M1} \cdot K}}{N}, \frac{s - \alpha - \beta + K \cdot (r_{M1} \cdot c_{M1} + r_{M2} \cdot c_{M2})}{K \cdot N \cdot (r_{M1} + r_{M2})}, 1 \right\} \end{cases},$$

where $s = 0$ in the *BASELINE* treatment and $s \in (\alpha, K)$ in the *SPILLOVER* treatment.

Appendix B

Sample Experimental Instructions

Dear participant,

Welcome to our experiment on decision-making. If you carefully follow these simple instructions, you may earn a considerable amount of money. The money you will earn in this experiment is yours to keep and will be paid to you **privately** and **in cash** at the **end of the experiment**. The experiment will last approximately **1 hour**. **Your payoff will depend on your decisions, the decisions of the other participants and the realization of random events.**

The experiment consists of two parts. You will receive separate instructions in the beginning of each part. These instructions will be read to you aloud and then you will have an opportunity to study them on your own. If you have a question about the content of the instructions, please raise your hand and the experimenter will answer your question **in private**. Please do not talk or communicate with other participants during the experiment.

You will receive a show-up fee of **€4** for arriving on time for the experiment. This show-up fee is yours to keep irrespective of your performance in the experiment.

At the end of the experiment, you **alone** will be informed about your private payoff from Part 1 and Part 2.

Good luck and thank you for your participation!

Part 1

You will receive **10 problems**. In each problem you need to choose between two lotteries. All 10 problems will appear on your computer screen at once. The example of a typical problem is given below:

Sample Problem N

Lottery X yields: €9 with probability 1/3 €2 with probability 2/3	Lottery Y yields: €4 with probability 2/3 €3 with probability 1/3
Which of the two lotteries would you choose?	
Lottery X	Lottery Y

Your payoff from this part will be determined **at the end of the experiment**, based on the outcome of the lotteries that you have chosen. First, a computer program will choose one participant in this room at random. This participant will blindly draw one card out of a box, containing ten cards numbered from 1 to 10. The number on the drawn card will determine one of 10 problems. This selected problem (together with your choice) will reappear on your computer screen. Then the computer program will choose another participant at random, who will blindly draw a card out of the box for lottery X. The monetary amount, written on this card, will be equal to the payoff for all participants, who have chosen Lottery X in the selected problem. An identical procedure will be implemented to determine the payoff for Lottery Y.

Example

For example, suppose that the computer program has selected one participant at random and he or she has drawn number **N** out of the box. **Problem N** presented above reappears on your screen. Then the second participant, randomly selected by a computer program, draws a card out of a box for Lottery X, which contains one card with €9 and two cards with €2 written on them. If you have chosen Lottery X in this problem, your payoff from this part will be equal to the monetary amount shown on the drawn card (either €9 or €2). After that, the computer program will select the third participant. This participant will blindly draw a card out of the box for Lottery Y, which contains one card with €3 and two cards with €4 written on them. If you have chosen Lottery Y in this problem, your payoff from this part will be equal to the monetary amount shown on the drawn card (either €3 or €4).

Your payoff from Part 1 will be paid out in cash at the end of the experiment along with your earnings from Part 2.

Part 2¹⁶

Part 2 of the experiment consists of **48 rounds**. In this part you will be asked to make decisions about entering competitive markets. You will be playing a game with all participants present in the room (**there are 14 participants in this room**). In the beginning of **each round** you will receive an endowment of **€3**.

Your task is to choose simultaneously with other participants and without communication with them whether you want to enter one or both of the following competitive markets or not. Market 1 can accommodate **C1** players and has a cost of entry of **€0.60**. Market 2 can accommodate **C2** players and has a cost of entry of **€0.06**. If you decide to enter a market, you would have to pay the cost of entry out of your endowment. In the beginning of **each round** you will see numbers **C1** and **C2** on your computer screen. You can think of **C1** and **C2** as capacities or sizes of Market 1 and Market 2 respectively. Note that the market with higher cost of entry is often smaller than the market with lower cost of entry.

You have to choose among the following four actions:

- enter Market 1 stay out of Market 2 (**M1**);
- enter Market 2 stay out of Market 1 (**M2**);
- enter Market 1 and Market 2 simultaneously (**M1 + M2**);
- stay out of both markets (**OUT**).

If you decide to stay out of both markets, you keep your endowment (**€3**).

The potential payoff from all possible actions (**M1**, **M2**, **M1 + M2** and **OUT**) is given in the tables 1, 2, 3 and 4 below and depends on the number of people, who decide to enter each market (the fewer people enter, the higher is your payoff). Note that all payoffs, in tables 1, 2, 3 and 4 represent your **final hypothetical payoff**. These payoffs already include the portion of your initial endowment, remained after you have paid the cost(s) of entry. **You do not need to make any additional calculations!**

Example

For example (see **Trial Table**) the computer screen shows that Market 1 can accommodate one player (**C1 = 1**) and Market 2 – thirteen players (**C2 = 13**). Assume that you think that only one **OTHER** player will enter Market 1, and five **OTHER** players will enter Market 2.

If your expectation is correct, according to the **Trial Table**:

- If you decide to enter Market 1 and stay out of Market 2 (action **M1**), you receive **€0**.

¹⁶ Here we provide sample instructions and tables for the *BASELINE* treatment. In the *SPILLOVER* treatment instructions are very similar. The only difference is that *SPILLOVER* instructions indicate that if participants choose an action $M1 + M2$ and if the payoff from this strategy is positive, they will receive a premium of €1.50. The tables also showed the premium of €1.50 for all positive final payoffs for action $M1 + M2$.

- If you decide to enter Market 2 and stay out of Market 1 (action **M2**), you receive **€23.94**. This payoff includes the remainder of your initial endowment after paying the cost of entering Market 2 (i.e. $€3 - €0.06 = €2.94$) and your profit from entering Market 2 (**€21**). Therefore, your final payoff from action **M2** is $€2.94 + €21 = €23.94$.
- If you decide to enter both markets simultaneously (action **M1 + M2**), you receive **€14.34**. This payoff includes the remainder of your initial endowment after paying the costs of entering Market 1 and Market 2 (i.e. $€3 - €0.60 - €0.06 = €2.34$) and your profit from both markets (**€12**). Therefore, your final payoff from action **M1 + M2** is $€2.34 + €12 = €14.34$.
- If you decide to stay out of both markets (action **OUT**), you retain your endowment from the beginning of the period and your payoff is **€3**.

Assume that you have decided to enter Market 2 and stay out of Market 1 (action **M2**). If one player (excluding you) enters Market 1 and five players (excluding you) enter Market 2, your hypothetical payoff in this round will be **€23.94**. If two players (excluding you) enter Market 1 and three players (excluding you) enter Market 2, your hypothetical payoff in this round will be **€29.94**. If four players (excluding you) enter Market 1 and nine players (excluding you) enter Market 2, your hypothetical payoff in this round will be **€11.94**. If nine players (excluding you) enter Market 1 and thirteen players (excluding you) enter Market 2, you will lose the remainder of your initial endowment (in this case $€3 - €0.06 = €2.94$) after costs and your hypothetical payoff in this round will be **€0**.

In the beginning of each round, you will see the description of both markets (numbers **C1** and **C2** and costs of entry) along with the number of the table, relevant for this round, on your computer screen. Be very careful – **C1**, **C2** and a table number may be different in each round!

After that, you will be asked to enter the number of players which you expect to enter Market 1 and Market 2. Then you will be asked to choose one of the actions (**M1**, **M2**, **M1 + M2** or **OUT**). All players are making their decisions simultaneously.

When all players have made their decisions, you will see the outcome on your computer screen. You will be informed about the total number of entrants to each market and the number of players, who stayed out of both markets as well as your hypothetical payoff in this round. You will be informed about your own hypothetical payoff only. You will not be able to see how much money other players have made.

Your payoff is called *hypothetical*, because at the end of Part 2 of the experiment, two randomly chosen players will blindly draw two numbers out of the box, which will contain 48 cards, numbered from 1 to 48. The numbers displayed on these cards mean the number of rounds. You will receive your payoff from these two rounds only. Therefore, two randomly drawn rounds will have real financial consequences for you.

At the end of the experiment you will receive your payoff from both parts of the experiment in cash. No other player will receive any information about your private payoff. We also ask you to fill out a brief questionnaire at the end of the experiment.