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Gender Robustness of Overconfidence and Excess Entry

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Abstract: Camerer and Lovallo (1999) present a thought-provoking experimental evidence that overconfidence might lead to excess entry into markets. As their findings are based on the majority of the sessions exclusively consisting of male participants, we replicate their experiment while including both men and women in all of our sessions. We are able to only partially replicate their main finding that the market entry decisions are driven by overconfidence. Surprisingly we also find that self-selection significantly decreases the entry rate. However, this is also where we observe gender differences in the entry rate – males who self-select into the experiment actually enter more often, which is in line with Camerer & Lovallo's observation. Our experiment thus points out that the overconfidence effect is sensitive to the participants' gender and experimental conditions.

JEL classifications: C9, C72, D2, D47
Keywords: Experiment, Gender, Market Entry, Overconfidence, Real Effort, Replication, Robustness

1 Introduction

Do optimistic biases predictably influence economic behavior of firms when entering into markets? A large body of psychology and social psychology literature documents that people are overconfident about their relative abilities or unreasonably optimistic about their future (Alicke, 1985; Dunning et al., 1989; Messick et al., 1985; Svenson, 1981; Taylor and Brown, 1988). Overconfidence of entrepreneurs and managers could therefore be crucial for understanding failures of new businesses. Camerer and Lovallo (1999; henceforth CL) present a thought-provoking experimental evidence that overconfidence might lead to excess entry into markets. As women are usually less overconfident than men (Lundeberg et al., 1994), CL findings are based on the majority of their sessions exclusively consisting of male participants.[1] With the increasing numbers of women managers, entrepreneurs and startup owners over the past decades, it is paramount to ascertain whether the excess entry finding is robust to a population consisting of both genders. We therefore replicate CL experiment while including both men and women in all of our sessions.

CL offer three possible explanations for business failures: (1) Quick exits that appear to be failures are actually hit-and-run entries that are profitable but brief. Profits are made if entering the market during the high peak, i.e. when profitability is high, and then leaving (or 'failing') when profitability dies down. Because of the fleeting nature of many business opportunities, a failure within a year of startup is probable and expected (Forbes, 2009). (2) Business entries are similar to lottery tickets, i.e. most firms expect to lose money and fail, but if they become successful, the payoff is large and worth the risk. Entrepreneurs understand the nature of risky entries and often report that the key to success is making profits on average rather than with every single investment. (3) Many entry decisions are simply mistakes due to underestimating the competitors or overconfidence about own abilities. Such mistakes are often hard to correct if the performance feedback is imperfect.

Distinguishing which one of the three explanations influences business failure and to what extent can be challenging with happenstance data. To explore the third explanation, CL design an economics experiment testing for the effect of overconfidence in one's skill on market entry decisions, i.e. whether overconfidence amplifies the market entry rate. In our study we use a mixed-gender subject pool to address the same two main questions as CL: 1. Is there more entry when people are betting on their own skill? 2. Are participants neglecting the reference group when they volunteer to participate in the experiment, knowing that their payoffs will depend on their skill? The answers to these questions deepen our understanding of the origins of business failures and can help designing better performance feedback mechanisms.

Overconfidence occurs when an individual's certainty that his predictions are correct exceeds the accuracy of those predictions (Klayman et al., 1999). Hoelzl and Rustichini (2005) identify three sources of overconfidence: people may overestimate their own abilities, perceive themselves more favorably than others perceive them, or perceive themselves more favorably than they perceive others. Indeed, a large body of psychology and social psychology literature provides evidence that people are overconfident about their relative abilities or unreasonably optimistic about their future (Alicke, 1985; Dunning et al., 1989; Messick et al., 1985; Taylor and Brown, 1988). The effect has been labelled "better than average".[2]

[1] CL's experiment consists of 8 sessions with both genders participating only in sessions 1 and 2. Sessions 3-8 were composed solely of male participants. CL use data from sessions 1-8 to analyze the link between overconfidence and excess entry as well as the impact of self-selection on entry decisions and data from sessions 3-8 to analyze whether the excess entry was caused by overconfidence or underestimating how many participants will enter the market in total.

[2] A popular example of overconfidence is asking a group of average people about their driving ability. Most of them will say they are above average even though only about half can be better than average (Svenson, 1981).

Related theoretical and empirical literature in economics and finance focuses on explaining economic phenomena and particular aspects of behavior associated with overconfidence (Bénabou and Tirole, 2002; Bénabou and Tirole, 2003; Daniel et al., 1998; Gervais and Odean, 2001; Weinberg, 2009). Overconfidence in one's skills or relative ability can, in financial markets, lead to excessive trading and lower returns (Barber and Odean, 2001), distortions in corporate investment decisions (Malmendier and Tate, 2005), value-reducing mergers (Roll, 1986) and to security market anomalies (Daniel et al., 1998). It has been shown to influence the estimation of one's own ability, performance (Clayson, 2005), level of control (Presson and Benassi, 1996), speed with which one can get work done (Buehler et al., 1994), accuracy of one's beliefs (Alpert and Raiffa, 1982; Klayman et al., 1999; Soll and Klayman, 2004; Healy and Moore, 2007) or even expert judgements such as the accuracy of diagnoses (Christensen-Szalanski and Bushyhead, 1981). Overconfidence thus appears to be a robust phenomenon present in a wide array of professional and business-related decisions, with market entry being one of them.

The experimental literature, to a great degree triggered by CL, identifies numerous factors, such as task difficulty (Hoelzl and Rustichini, 2005; Moore and Cain, 2007) leading to overconfidence. An example of such task where overconfidence plays an important role is the introduction of risky products to the market (Simon and Houghton, 2003). Similarly, greater overconfidence tends to lead to aggressive behavior in the pursuit of higher wealth (Deaves et al., 2009). Interestingly, experience and specialization can, in some scenarios, contribute to overconfidence; for example studies by Kirchler and Maciejovsky (2002); Glaser et al. (2005); Glaser et al. (2007) show that experts are more likely to be overconfident than relatively inexperienced subjects. However, some other studies find that overconfidence tends to decrease with experience (Christoffersen and Sarkissian, 2002; Gervais and Odean, 2001; Locke and Mann, 2001). The evidence on gender effects in overconfidence is also mixed as the findings appear to vary with the task, activity, and/or environment. For example, Beyer (1990) observes that the tendency to ascribe success to personal effort and failure to external forces is less pronounced in women, while Deaves et al. (2009) find little evidence that gender influences trading activity, hinting that more research is necessary to understand the prevalence of overconfidence and its driving factors. Testing market entry decisions in a population composed of both genders is a step in this direction.

CL's design allows one to identify whether market entry is driven by overconfidence. Whether an entry is successful or not depends on the market capacity and the entrant's rank. In one scenario, the rank is determined by performance in a task and thus the decision whether to enter depends on one's confidence in his skills relative to others. In the control scenario, the rank is determined randomly. CL find that when payoffs from entry depend on skills, excess entry is higher than when payoffs are determined randomly, providing evidence of overconfident behavior. Furthermore, excess entry is highest when the participants are told in advance that their payoffs will depend on their skill, suggesting that participants neglect consideration of the reference group with which they will be competing.[3] CL use expected average profits to distinguish whether the excessive entry was caused by overconfidence or underforecasting and find that overconfidence is the main driver.

To the best of our knowledge, there is no study testing the robustness of the CL's finding with respect to both genders. Including female participants, who have been shown to be less overconfident than males in various other contexts, constitutes a more conservative test of the effect of overconfidence on market entry decisions and is a step towards increasing the external validity of CL's results. Our study differs from CL also in two procedural aspects; our experiment is fully computerized (as opposed to pen and paper) and instead of solving puzzles

[3] Reference group neglect is also known in the literature as egocentrism (Kruger, 1999; Windschitl and Chambers, 2004).

as in CL, our participants solve mazes. Finally, we use better suited methods to analyze the collected data.[4] Design parameters, session ordering, and procedures (to the extent known to us) remain the same.

In our experiment, we only partially obtain the same results as CL. While we find a mixed evidence that the industry profit is lower in skill-rank rounds than in random-rank rounds due to more entry in the skill-rank rounds, we do not find that self-selected participants are more overconfident and find no difference in expected average profits between random-rank and skill-rank rounds, suggesting that overconfidence might not be as strong of a driving factor of entry decisions when both genders are represented amongst the market participants.

2 Experimental design and procedures

CL employ the market entry game introduced by Selten and Güth (1982) to study the link between overconfidence and decisions to enter the market.[5] In what follows we present the CL modification of the game with rank-based payoffs. Our experiment design follows CL in terms of the implemented parameters, session ordering, and procedures to the extent known to us. Any differences are discussed below.

In the repeated market entry game, each participant is endowed with $10 and is informed about the market capacity "c", where 0< c <15 (for the capacity in each round used in the same sequence in both CL and our experiment, see Table C1 in Appendix C). The participants then simultaneously choose whether to enter the market or not each round. The payoff to the entrants depends on the overall number of entrants, pre-announced market capacity c and the entrant's rank. Entrants ranked below c lose their initial endowment, while entrants ranked c or above earn a positive sum of money (see Table 1). The top c entrants share $50 proportionally, with higher-ranking entrants earning more relative to other entrants.[6] Non-entrants do not earn or lose any money; they keep their initial endowment.

The rank is assigned randomly or based on the participant's skill as determined by performance in a real-effort task. In particular, skill-ranks are determined by the speed of finishing five mazes (sessions 1 and 2) or by the number of correct answers on a trivia quiz about sports and current events (sessions 3-8).[7]

[4] Namely, we construct a normalized entry rate to compare data across sessions that do not have the same capacities in each round; more on this in Results section.
[5] For a theoretical analysis of the standard version of the market entry game and a recent review of the empirical literature see Collins et al. (2017).
[6] If the number of entrants is lower than c, the entrants share $50 proportionally, i.e. the entrant with the lowest rank receives the smallest $ amount, the entrant with the second lowest rank receives twice as much as the previous one etc.
[7] CL's design involved solving ten puzzles, details of which were not reported in the paper. Instead of puzzles, our participants solve mazes, which is a somewhat comparable task in terms of skills. We calibrated the number of mazes to five based on the expected time (10 minutes) it would take the participants to solve them. Our objective was to implement a task that would require display of skills but that would not unnecessarily prolong the experimental session.

Table 1. Rank-based payoffs*

Rank	Market Capacity			
	c=2	c=4	c=6	c=8
1	33	20	14	11
2	17	15	12	10
3		10	10	8
4		5	7	7
5			5	6
6			2	4
7				3
8				2

* Payoff in $ for successful entrants as a function of "c"

The game is played in two blocks, each consisting of 12 rounds (24 rounds in total). In one of the two blocks the rank is determined randomly (R), in the other block the rank depends on skills (S). This feature is implemented in a within-subject design, i.e. the same participants participate in both blocks of rounds. Participants are told in advance in which block of rounds the rank is assigned randomly and in which it depends on their skill. To control for order effects, in half of the sessions the block of rounds with random rank is run first, followed by the block of rounds with skill-dependent rank. In the other half of the sessions the order is reversed, i.e. the block of rounds with skill-dependent rank is run first and the random rank second. With the exception of sessions 1 and 2 as the in the original CL experiment, the random-rank rounds have the exact same order of c's as the skill-rank rounds and thus the two blocks are directly comparable.

Along with their individual entry decisions, participants forecast how many entrants they expect in that round. For each correct forecast, the participants earn $1. CL use these forecasts to distinguish between participants who enter because they underestimate the number of competitors and participants who are overconfident about their skills and who therefore enter because they think their performance on the quiz or maze is better than average. Participants' ranks are not revealed until the end of the experiment, i.e. after their market entry decisions for all 24 rounds.

A total of 118 participants, 59 males and 59 females, took part in the experiment. The experimental sessions were conducted in the New Zealand Experimental Economics Laboratory (NZEEL) at the University of Canterbury. Participants were recruited using the online database system ORSEE (Greiner 2015). Each participant only participated in a single session of the study, and had not participated in any similar market entry experiment run at NZEEL.

The invitation, similarly as in CL, differed in information provided to the participants before signing up for the experiment. In sessions 1-4 the participants were invited to participate in the experiment with an opportunity to make money. In addition to that, in sessions 5-8, the participants were told in the invitation email that their payoff in the experiment would depend on their skills, especially their knowledge about current events and sports.[8] In these latter sessions it was possible for participants confident of their abilities to self-select into the experiment (see Table 2 for the session overview).

[8] CL do not report the details how their participants were invited to the experiment or what the communication channel was. The information included in the invitation email to participants in our database was as follows: "Earn money in an experiment in which performance on sports and current events trivia will determine your payoff. If you are very good you might earn a considerable sum of money." The latter part of the sentence is reproduced from the CL paper.

Unlike CL experiment, our experiment was fully computerized (i.e. including the mazes) using z-Tree (Fischbacher, 2007). The number of participants in a session varied from 12 to 16. All sessions were run under a single-blind social distance protocol in which there was a complete anonymity between participants but not with respect to the experimenter. On average, a session lasted 50 minutes including the payment. The participants earned 13.80 NZD on average.[9]

Upon entering the laboratory, participants were asked to sit in a cubicle of their choice. At the beginning of the experiment instructions (provided in Appendix A) were handed out, as well as projected onto a screen and read aloud by the experimenter. Participants then had a few minutes to go through the instructions again, this time in their own pace. Any questions arising were answered in private. All participants had to answer the control questions (provided in Appendix B) correctly before they could proceed to the decision-making part of the experiment. This procedure allowed us to assess the understanding of instructions and clarify any confusion. After the control questions, participants first entered their decisions in each of 24 rounds and only then engaged in a task that determined their rank for the skill based rounds. Upon the completion of the experiment, they were also asked to fill out a questionnaire. Participants were then called one by one to receive their payment in private in the control room at the back of the laboratory.

Table 2. Experimental sessions

Session #	n	Invitation	Block Order	Skill
1	12	No self-selection	R/S	Maze
2	14	No self-selection	S/R	Maze
3	16	No self-selection	R/S	Quiz
4	16	No self-selection	S/R	Quiz
5	16	Self-selection	R/S	Quiz
6	16	Self-selection	S/R	Quiz
7	14	Self-selection	R/S	Quiz
8	14	Self-selection	S/R	Quiz

R= random-rank, S=skill-rank

3 Hypotheses

Using data from our experiment we test the original CL's hypotheses.

Hypothesis 1: There is lower industry profit (and thus more entry) in skill-rank rounds than in random-rank rounds.

If participants are overconfident, they will enter the market more often in skill-rank rounds, which will result in lower industry profits, i.e. if the number of entrants is higher than c, the industry profit will be negative.

Hypothesis 2: The profit differential between skill-rank and random-rank rounds in four sessions with self-selection is larger than in the remaining four sessions with no self-selection.

[9] For reference, at the time of the experiment 1 NZD = 0.7883 USD and the adult minimum wage in New Zealand was 14.25 NZD per hour.

The larger the skill-rank and random-rank profit differential, the more entry will be observed in the skill-rank rounds. If the entrants neglect the reference group, i.e. enter more because of overconfidence in their skill but ignore that all other entrants are doing the same, the differential between the skill-rank and random-rank will be larger in sessions with self-selection than in session with no self-selection.

Hypothesis 3: The expected average profit is smaller in skill-rank rounds than in random-rank rounds.

The expected average profit is calculated based on the forecasts of participants. If participants decide to enter because they think fewer people will enter, then the expected average profit will be higher in skill-rank rounds than in random-rank rounds. If, however, participants enter more often because they are overconfident about their relative skills, the expected average profit will be lower in skill-rank rounds than in random-rank rounds.

4 Results

The section is organized as follows: We (attempt to) replicate CL's results by applying the tests they use to our data. These results are always reported first. It is important to note that in CL's design (which we replicate) sessions 1 and 2 have a different order of c's across rounds. That is, participants in session 1 face a different order of c's than participants in session 2, making these two sessions not directly comparable. To rectify the issue, in addition to CL's analysis, we (i) analyze data only from sessions 3-8 and (ii) we calculate the normalized entry rate that addresses the different order of c's in sessions 1 and 2 and thus allows us to perform tests on data from all sessions (i.e. 1-8).

The industry profit, calculated by adding profits of successful entrants and losses of unsuccessful entrants in a given round, is strictly positive in 81 (=84%) and negative in 5 out of 96 random-rank rounds (12 rounds/session x 8 sessions = 96 observed rounds in each block). The industry profit is zero in the remaining 10 random-rank rounds. The average industry profit across random-rank rounds is $29.28. In the skill-rank rounds the industry profit is strictly positive in 76 (=79%) and negative in 9 out of 96 rounds. The average profit across skill-rank rounds is $26.14.

4.1. Industry profit and market entry

Hypothesis 1 states there will be a lower industry profit (resulting from more entry) in the skill-rank rounds than in the random-rank rounds. The hypothesis is based on a conjecture that when participants are betting on their own skill they will enter more often, which will in turn lower the total industry profit.

Following CL, we first test for differences in the industry profit between the skill-rank and random-rank rounds using a matched pairs t-test.[10] Recall that each experimental session consists of two blocks composed of twelve random-rank and twelve skill-rank rounds. The test is conducted as follows. The industry profit from the first twelve random-rank rounds in session 1 is matched with industry profit from the first twelve skill-rank rounds in session 2. Similarly, the industry profit from the skill-rank rounds in session 3 is matched with the industry profit

[10] We report the t-test in order to make our results easily comparable with CL.

from the random-rank rounds in session 4. In the same way session 5 with 6, and 7 with 8 are matched. In sessions 3-8, each pair of rounds being compared has the same value of c's, the same history (or path) of previous values of c's, and differs only in how the rank was determined. We followed this procedure in order to replicate the original design by CL and so preserved the order of c's in sessions 1 and 2. The matched pairs t-test does not detect a difference between profits in the random-rank rounds and the skill-rank rounds (p-value=0.193). Our result differs from the one obtained by CL who find that the industry profit is significantly lower in the skill-rank rounds than in the random-rank rounds when using individual data from sessions 1-8 (CL's p-value < 0.001).

The fact that participants in session 1 face a different order of c's than participants in session 2, makes these sessions not directly comparable. We thus exclude these two sessions from the matched pairs t-test. The t-test for sessions 3-8 supports CL's finding that there is more entry in the skill-rank rounds (i.e. more overconfidence in one's skill) as the industry profits are lower in the skill-rank than in the random-rank rounds (p-value=0.084) albeit this effect is not as strong as in CL.

In order to be able to use the data from sessions 1 and 2 (which do not have the same order of c's) we calculate a normalized entry rate. The normalized entry rate is the ratio of the number of entrants and the actual capacity c in the respective round, where 100% means that the number of entrants was exactly the same as c in the given round. If the normalized entry rate is higher than 100%, there are more entrants than c. If it is less than 100%, the market is not saturated and it is possible for more participants to enter the market and make profit. By calculating the normalized entry rate we are able to control for different c's in the given round between sessions 1 and 2. Using the normalized entry rate we then test whether there is more entry (a higher normalized entry rate) in the skill-rank rounds than in the random-rank rounds. The t-test does not detect a statistically significant difference in normalized entry rates between the skill-rank and random-rank rounds (p-value=0.482).

In addition to tests reported by CL, one can also test for within-subject comparisons as each participant took part both in the random-rank and skill-rank rounds. To test whether there is a difference in industry profit as well as in normalized entry rates between random-rank rounds and skill-rank rounds within a session we use the Wilcoxon rank sum test; p-values for each session are reported in Table 3 below. Except for the industry profit in session 6, where the profit in the random-rank rounds is weakly statistically higher than in the skill-rank rounds, none of the other tests show that industry profits are different in the random-rank rounds than in the skill-rank rounds of the same session.

In summary, using participants of both genders we find mixed evidence of excess entry due to overconfidence when comparing behavior in the skill-rank compared to the random-rank rounds.

Table 3. The Wilcoxon matched-pairs signed-ranks test for the difference in industry profits and normalized entry rate between the random-rank and the skill-rank rounds within subjects

Session #	Random-rank	Skill-rank	Wilcoxon rank sum test (p-value)	Random-rank [%]	Skill-rank [%]	Wilcoxon rank sum test (p-value)
1	370	450	0.310	140.0	131.8	0.843
2	330	260	0.478	176.4	189.7	0.3762
3	180	120	0.174	241.7	240.3	0.237
4	330	310	0.657	191.0	195.1	0.693
5	400	370	0.250	158.3	173.0	0.172
6	330	160	0.012	184.0	231.3	0.009
7	340	330	0.809	165.7	171.9	0.691
8	530	510	0.657	94.9	108.8	0.265

4.2. Reference group neglect

Hypothesis 2 states that the profit differential between the skill-rank and random-rank rounds in sessions with self-selection is larger than in sessions without self-selection due to the reference group neglect.

Following CL, we first conduct a matched pairs t-test comparing the skill-random profit differential between sessions 1-4 (without self-selection) and 5-8 (with self-selection), the result of which does not support Hypothesis 2 (p-value=0.432). This finding stands in contrast with the one obtained by CL who observe that the reference group neglect produces a significantly larger skill-random rank entry differential in sessions with self-selected participants than in sessions without self-selection (p-value < 0.001); see Table 4 for a comparison of our results with CL.

In addition to the test performed using data from sessions 1-8 as in CL, we run a matched pairs t-test comparing the skill-random profit differential between sessions 3-4 and 5-8 (i.e. excluding sessions 1 and 2 that have different order of c's). This test also does not support the hypothesis that differential is larger in sessions with self-selection than without (p-value=0.659).

In summary, applying the t-test (used by CL) to our data, we find that the profit differential between skill-rank and random-rank rounds is not larger in sessions with self-selection than without self-selection, pointing out that overconfidence does not increase with self-selection in a population composed of both genders

Table 4. Comparison of CL's results vs. ours

	CL (sessions 1-8)	Our study (sessions 1-8)	Our study (sessions 3-8 only)
Avg. profit random-rank	$16.87	29.27	$29.31
Avg. profit skill-rank	$-1.56	$26.15	$25.00
Matched pairs t-test	t=-7.43 p<0.001	t=1.311 p=0.193	t=1.755 p=0.084
Avg. profit without self-selection, random-rank	$19.79	$25.21	$21.25
Avg. profit without self-selection, skill-rank	$10.83	$23.75	$17.92
Avg. profit self-selection, random-rank	$13.96	$33.33	$33.33
Avg. profit self-selection, skill-rank	$-13.13	$28.54	$28.54
Matched pairs t-test	t=-4.08 p<0.001	t=0.793 p=0.432	t=-0.447 p=0.659

4.3 Expected profit differential in skill and random rounds

The results in the previous subsections provide mixed evidence for overconfidence resulting in excess entry, and demonstrate that unlike in CL, in our experiment self-selection does not increase the strength of the overconfidence effect. These tests, however, do not control for all possible explanations. Excessive entry in the skill-rank rounds may not necessarily be due to overconfidence about one's skills, but due to the underestimating how many participants will enter in total (CL call this the "blind spot" hypothesis). If the number of expected entrants is underestimated, it decreases the participants' payoffs because they enter even though they should not. In order to test whether the expectations are correct, we ask participants to saliently forecast the number of entrants in each round.[11]

On average, the number of forecasted entrants in all sessions is 6.07 and 6.23 entrants in random-rank and skill-rank rounds, respectively. The actual number of entrants in all sessions is on average 5.75 and 6.26 for the random-rank rounds and the skill-rank rounds, respectively (see Figure 1 in Appendix C). The difference between forecasted and actual entrants in the random-rank rounds is not statistically significantly different (Mann-Whitney p-value=0.599)[12]. In the skill-rank rounds this difference is not statistically significant either (Mann-Whitney p-value=0.916). In the random-rank rounds participants forecast about 0.32 entrants too high and in the skill-rank rounds their forecast is converging to the actual number of entrants.

[11] The specific question we asked before each round is: "How many people (including yourself) do you expect to enter the market in this round?" If a participant forecasted the number of entrants correctly, $1 was added to his/her payoff in the respective round.

[12] CL only report a regression in which they use data from sessions 3-8.

To separate overconfidence from incorrect estimates of others' entry CL use the obtained forecasts to compute the profit that a participant expects the average entrant to earn, calculated in a following way:

$$E_j(\pi_{ijt}) = (50\text{-}10^*(F_{ijt} - c_{it}))/ F_{ijt}, \quad (1)$$

where $E_j(\pi_{ijt})$ is the expected average profit, F_{ijt} is the forecast of participant j used to calculate the profit that participant j expects the average entrant to earn, and c_{it} is the capacity in the particular round.

Separating overconfidence from incorrect estimates of others' entry requires testing the hypothesis that the expected average profit is larger in the random-rank rounds than in the skill-rank rounds. If participants decide to enter in the skill-rank rounds because they think that fewer other participants will enter, the expected average profit in the skill-rank rounds will be larger. Including $E_j(\pi_{ijt})$ in the entry regression, reported in the next subsection, will separate out the effect falsely attributed to skill. If, on the other hand, the participants enter because they are more overconfident in the skill-rank rounds compared to the random-rank rounds, not taking into account the number of entrants they expect to enter, the expected average profits will be smaller in the skill-rank rounds than in the random-rank rounds. The overconfident participants will expect to earn more than the average entrant and enter even when the expected average profit is low.

Following CL, we therefore calculate the differential between expected average profits in the random-rank rounds (denoted π_r) and in the skill-rank rounds (denoted π_s), using only the rounds in which participants entered. A negative differential, i.e. larger profits in the skill-rank rounds than in the random-rank rounds, represents the incorrect estimation of entrants, whereas a positive differential represents overconfidence. In Table 4 we report the mean differential $\pi_r - \pi_s$, averaged across entering participants, the number and percentage of participants who have a negative mean (i.e. who expect less average profit in the skill-rank rounds), and the number and percentage of participants whose expected average profit is negative, on average, across the random-rank rounds and skill-rank rounds. For completeness, in rows 3 and 4 we also report a percentage of entrants whose profit is lower than 0 in the random-rank rounds and the skill-rank rounds.

The mean differential $\pi_r - \pi_s$ is negative in sessions 1 and 2, suggesting an incorrect estimation of number of entrants by participants, and positive in sessions 3 and 4, suggesting the presence of overconfidence. In session 1, 44% of the participants expect to earn less in the skill-rank rounds than in the random-rank rounds. In sessions 2, 3 and 4, it is respectively 57%, 46% and 67% of participants. In the self-selection sessions 5-8, the mean differential $\pi_r - \pi_s$ is negative in all sessions, except for session 8, where the differential is positive and suggests the presence of overconfidence. In session 5 only 18% of the participants expect to earn less in the skill-rank rounds than in the random-rank rounds. In session 6, 7 and 8 it is 57%, 38% and 75%, respectively. The t-test does not detect a significant difference in the average differential of expected profits per person between the self-selection sessions and the no self-selection sessions (p-value=0.913). In other words, there is no difference in the expected average profit between the skill-rank rounds and the random-rank rounds.

Table 4. The average differential in expected profits per entrant between the random-rank and skill-rank rounds

Measure	Session 1	Session 2	Session 3	Session 4	Session 5	Session 6	Session 7	Session 8	Total
Πr - Πs	-1.126	-0.665	0.023	1.832	-1.094	-0.886	-1.718	4.483	1.036
# of entrants with Πr - Πs<0 (percent)	5/9 (56%)	6/14 (43%)	7/13 (54%)	4/12 (33%)	9/11 (82%)	6/14 (43%)	8/13 (62%)	2/8 (25%)	47/94 (50%)
# of entrants with Πr <0 (percent)	0/9 (0%)	0/13 (0%)	3/12 (25%)	1/11 (9%)	0/10 (0%)	0/11 (0%)	0/12 (0%)	0/8 (0%)	4/86 (5%)
# of entrants with Πs <0 (percent)	0/8 (0%)	1/14 (7%)	0/11 (0%)	2/12 (17%)	0/11 (0%)	2/14 (14%)	0/13 (0%)	0/8 (0%)	5/91 (5%)

4.1 Logistic regression

Table 5 reports a fixed-effects logistic regression of the entry decision. In line with the t-test results using the industry profits as well as the normalized entry rates, we find that the entry rate in the skill-rank rounds is not higher than in the random-rank rounds. While one might think that excess entry by males, as observed in CL, is offset by females entering significantly less often, this is not what we find in our data; as per the regression results, being male does not affect the entry rate.

Unlike the results of the t-test, our regression results show that participants who received an invitation email saying that their payoffs in the experiment (variable Self-selection in the regression) will depend on their skills enter less than those who received a generic invitation email without such information (which is in stark contrast to CL). Curiously, this is where we do observe gender differences -- the coefficient associated with the interaction term of being male and self-selection is positive and highly statistically significant, meaning that males in self-selection sessions enter more often (48%) than females (27%). The difference in entry rates of males and females is highly statistically significant (p-value < 0.001; chi-square test).

Similarly to CL, we also find the effect of the expected profit to be negative and significant. CL hypothesize that this is due to subjects planning to enter and forecasting a lot of entry, so the expected average profit is lower when they enter and relate the explanation to the false consensus effect in which people use their own decision as a clue about what others will do. Finally, economics students enter less often than non-economics and participants in sessions with the mazes enter more often than participants in sessions with the quiz.

Table 5. Fixed effects logistic regression of the entry decision

	Selected demographics			All Demographics		
Variable	**Coefficient (Robust Std. Err)**	**Marginal**	**z-statistic (p-value)**	**Coefficient (Robust Std. Err)**	**Marginal**	**z-statistic (p-value)**
Intercept	-0.113		-0.47	-0.413		-0.94
	(0.241)		(0.639)	(0.440)		(0.349)
C	-0.030	-0.007	-1.24	-0.026	-0.005	-1.04
	(0.024)		(0.213)	(0.025)		(0.299)
$E(\pi_{ijt})$	-0.015***	-0.004	-3.50	-0.016***	-0.003	-3.58
	(0.004)		(0.001)	(0.005)		(0.001)
Skill	0.078	0.033	0.70	0.086	0.033	0.76
	(0.110)		(0.482)	(0.112)		(0.445)
ECON	-0.489***	-0.111	-5.66	-0.429***	-0.091	-4.44
	(0.086)		(0.001)	(0.096)		(0.001)
Self-selection	-0.825***	-0.053	-5.31	-0.991***	-0.084	-5.85
	(0.155)		(0.001)	(0.170)		(0.001)
Male	0.001	0.113	0.00	0.011	0.108	0.09
	(0.112)		(0.998)	(0.125)		(0.932)
Maze	0.244**	0.056	2.11	0.148	0.032	1.24
	(0.116)		(0.035)	(0.120)		(0.216)
Age				-0.067***	-0.014	-6.52
				(0.010)		(0.001)
Non New Zealander				-0.090	-0.019	-0.76
				(0.118)		(0.447)
Siblings				0.137***	0.029	4.20
				(0.033)		(0.001)
Relative Income				-0.138**	-0.029	-2.42
				(0.057)		(0.015)
City size				0.530***	0.112	10.36
				(0.051)		(0.001)
Living with others				0.106***	0.023	4.04
				(0.026)		(0.001)
Money				0.001	6.50e-06	0.33
				(0.001)		(0.743)
Finance study				0.0002	0.001	0.16
				(0.0013)		(0.873)
Rely				-0.021	-0.005	-1.21
				(0.018)		(0.225)
Order	0.142*	0.032	1.79	0.289***	0.061	3.34
Random/Skill	(0.080)		(0.074)	(0.086)		(0.001)
Self-	0.134		0.85	0.140		0.86
selection*Skill	(0.158)		(0.395)	0.162		(0.390)
Self-	0.998***		6.16	1.004***		5.46
selection*Male	(0.162)		(0.001)	(0.184)		(0.001)
Round dummy	yes			yes		
Log-likelihood	-1830.875	Pseudo R2=0.0434		-1737.1825	Pseudo R2=0.0923	

Sessions 1-8 (CL report sessions 3-8; we provide such regression in Table C2 in appendix C), n=2832, standard errors are not clustered at the session level because of a small number of sessions.
Run on StataSE 13.0. Robust standard errors used. Round 24 is the omitted control variable.
*, **, *** refer to statistical significance at the 10%, 5% and 1% levels, respectively.
Description of demographic variables: non New Zealander represents participants who are not from New Zealand; siblings represents number of siblings; relative income represents income far below avg., below avg., average, above avg. or far above avg. (from 1 to 5). City size, living with others, money, finance study and rely represent the size of the city from 2000 to 100 000+; number of people in a household, share of monthly expenses one finances alone; reliability of the data provided - 9 being most reliable.

5 Discussion

CL propose a novel idea that business failures might be caused by overconfidence of those who decide to enter the market. In testing their conjecture, they find that males overconfident about their skills are more likely to enter the market and that overconfidence increases with self-selection. In the current experiment, we seek to replicate CL using a sample composed of both genders, making it a more conservative, and given the increased number of female managers and entrepreneurs observed in recent years also more timely test of their conjecture. Apart from including both genders in all our sessions and running the experiment with the use of computers, we tried to keep the design and procedures as close as possible to CL. We analyze our data the same way as CL do and augment their approach by adding more suitable tests that allow us to properly utilize the entire data sample.

Our results differ somewhat from CL as we were able to only partially replicate their finding that the industry profit is lower and thus that there is more entry in the skill-rank compared to the random-rank rounds. When we compare the profit differential between the skill-rank and random-rank rounds using the t-test (as in CL), its results indicate that overconfidence does not increase with self-selection in a population composed of both genders. Regression results, on the other hand, show that self-selection significantly decreases the entry rate, which is in stark contrast to CL. However, this is also where we observe gender differences in the entry rate – males who self-select into the experiment enter more often, which is in line with CL's observation. We also find that when participants are expecting higher profits, they enter less often, which is the same result as in CL. Finally, we observe no difference between entry caused by incorrect estimates of others' entry or overconfidence in the sessions with or without self-selection.

Apart from the above-described differences between our experiment and CL, there might be additional reasons for the diverging results. First and foremost, our experiment was conducted in New Zealand as opposed to the U.S., some 20 years later than the original CL study. New Zealand students have a tendency to be rather shy whereas US students known to be quite outspoken, which could have contributed to their decisions (and confidence) in the experiment. Second, CL procedures are described to the experimental economics standard and as such they do not include details regarding, for example, how the participants were recruited for the sessions or what the quiz questions or puzzles were, since from the perspective of the research question these individual features are unlikely to play a role. However, as seen in other areas of experimental research, for example dictator games, the results are often sensitive to a variety of seemingly innocuous variations (Cooper and Kagel, 2009). It is therefore possible that our procedures deviated from the original ones to some extent and these minor procedural differences have in turn affected the observed behavior. The lesson in all this is that the overconfidence effect is sensitive to the participants' gender and experimental conditions.

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Appendix A Instructions
Session 1 and 2

INSTRUCTIONS

No Talking Allowed
Now that the experiment has begun, we ask that you do not talk. If you have a question after we finish reading the instructions, please raise your hand and the experimenter will approach you and answer your question in private.

Anonymity
The identity of the participants will not be revealed to other participants at any time during the experiment.

Show-up Fee
If you agree to participate in the experiment you will be given $5, which is yours to keep.
Structure of the Experiment
This experiment is computerized. If you have any problems entering your decision, please alert the experimenter. The experiment involves two sets of decisions. Each set of decisions consists of 12 rounds (i.e. 24 rounds in total). These two sets differ in how the rank is determined.
In the first 12 rounds your rank will be determined by your speed of finishing the mazes (as will be explained later). In the second 12 rounds your rank will be determined randomly.
(Session 2 instructions read: In the first 12 rounds your rank will be determined randomly. In the second 12 rounds your rank will be determined by your speed of finishing the mazes (as will be explained later)).

In each round you are asked to decide whether to enter the market or not. In the beginning of each round the market capacity "c" for that round will be announced. You can think of "c" as the size of the market. You will also be informed about the number of entrants in the previous round.

Decision Making Task
In each round you start with $10.
If you decide not to enter the market, you earn nothing and lose nothing; your earnings for that round will be $10.
If you decide to enter the market, your payoff in each round will depend on your rank relative to the ranks of other participants who entered the market and on the capacity "c".

If you entered the market
Your rank and the capacity for that round determine if you are a successful or unsuccessful entrant. If your rank is less than or equal to the capacity, then you are a successful entrant. If your rank is greater than the capacity, then you are an unsuccessful entrant. The unsuccessful entrant will lose the $10 (s)he was given in the beginning of that round. The payoffs of successful entrants as a function of "c" are shown in the table below.

ONE of all 24 rounds will be chosen randomly and your rank and decision in this round will determine your payoff.

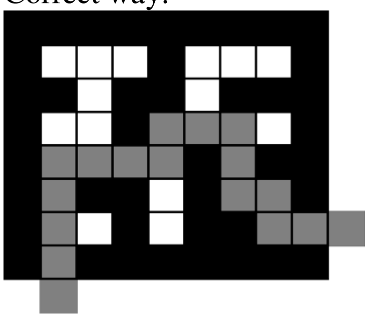
Rank	Capacity			
	2	4	6	8
1	33	20	14	11
2	17	15	12	10
3		10	10	8
4		5	7	7
5			5	6
6			2	4
7				3
8				2

All participants will take part in both sets of decisions in the same order. In each round you will be also asked to estimate the number of people (including you) that you expect to enter the market in that round. If your estimation of the number of entrants is the same as the actual number of entrants in that round, additional $1 will be added to your payoff in that round.

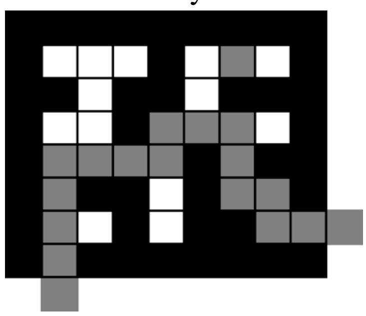
The Maze

After you finish all 24 rounds in the decision making task, you will be given five mazes to solve. You need to find the shortest way from one end of the maze to another. If you have highlighted all the correct squares in the maze, the OK button will pop up. Click OK in order to continue. The participant, who finishes the mazes the fastest, will be ranked number 1. A participant, who is the second fastest, will be ranked number 2 and so on.

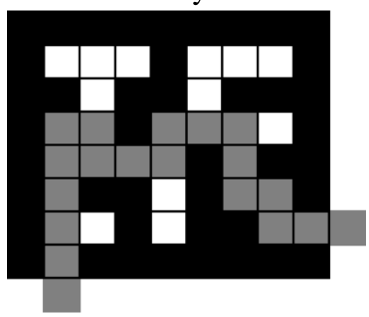
Correct way:



Incorrect way:



Incorrect way:



Example

Suppose "c" is 2 and four participants decide to enter the market. The entrant with rank number 1 earns $33 and the entrant with rank number 2 earns $17. The entrants with rank number 3 and number 4 lose $10, i.e. their payoff for that round will be 0.

Payment of Experiment Earnings

ONE of all 24 rounds will be chosen randomly and your rank and decisions in this round will determine your payoff.

All money will be paid to you in cash at the end of the experiment. Because your decision is private, we ask that you do not tell anyone your decision or your earnings either during or after the experiment. We also ask you to not gather near the lab after you receive your payment.

Are there any questions?

Sessions 3-8

INSTRUCTIONS

No Talking Allowed
Now that the experiment has begun, we ask that you do not talk. If you have a question after we finish reading the instructions, please raise your hand and the experimenter will approach you and answer your question in private.

Anonymity
The identity of the participants will not be revealed to other participants at any time during the experiment.

Show-up Fee
If you agree to participate in the experiment you will be given $5, which is yours to keep.

Structure of the Experiment
This experiment is computerized. If you have any problems entering your decision, please alert the experimenter. The experiment involves two sets of decisions. Each set of decisions consists of 12 rounds (i.e. 24 rounds in total). These two sets differ in how the rank is determined.
In the first 12 rounds your rank will be determined randomly. In the second 12 rounds your rank will be determined by your score on a quiz (as will be explained later).
(Sessions 4, 6 and 8 read: In the first 12 rounds your rank will be determined by your score on a quiz (as will be explained later). In the second 12 rounds your rank will be determined randomly.)

In each round you are asked to decide whether to enter the market or not. In the beginning of each round the market capacity “c” for that round will be announced. You can think of “c” as the size of the market. You will also be informed about the number of entrants in the previous round.

Decision Making Task
In each round you start with $10.
If you decide not to enter the market, you earn nothing and lose nothing; your earnings for that round will be $10.
If you decide to enter the market, your payoff in that round will depend on your rank relative to the ranks of other participants who entered the market and on the capacity “c”.

If you entered the market
Your rank and the capacity for that round determine if you are a successful or unsuccessful entrant. If your rank is less than or equal to the capacity, then you are a successful entrant. If your rank is greater than the capacity, then you are an unsuccessful entrant. The unsuccessful entrant will lose the $10 (s)he was given in the beginning of that round. The payoffs of successful entrants as a function of “c” are shown in the table below.

ONE of all 24 rounds will be chosen randomly and your rank and decision in this round will determine your payoff.

Rank	Capacity “c”			
	2	4	6	8
1	33	20	14	11
2	17	15	12	10
3		10	10	8
4		5	7	7
5			5	6
6			2	4
7				3
8				2

All participants will take part in both sets of decisions in the same order. In each round you will be also asked to estimate the number of people (including you) that you expect to enter the market in that round. If your estimation of the number of entrants is the same as the actual number of entrants in that round, additional $1 will be added to your payoff in that round.

The Quiz
After you finish all 24 rounds in the decision making task, you will be asked to participate in a multiple choice quiz. There are 30 sports & current events questions in the quiz, each question has only one correct answer. You will have 10 minutes to answer all questions. A participant with the most correct answers will be ranked number 1, etc. If two or more participants correctly answered the same number of questions, the ties will be broken by the shorter amount of time taken to answer all questions.
Example
Suppose “c” is 2 and four participants decide to enter the market. The entrant with rank number 1 earns $33 and the entrant with rank number 2 earns $17. The entrants with rank number 3 and number 4 lose $10, i.e. their payoff for that round will be 0.

Payment of Experiment Earnings
ONE of all 24 rounds will be chosen randomly and your rank and decisions in this round will determine your payoff.
All money will be paid to you in cash at the end of the experiment. Because your decision is private, we ask that you do not tell anyone your decision or your earnings either during or after the experiment. We also ask you to not gather near the lab after you receive your payment.
Are there any questions?

Appendix B Control Questions

1. How much would you earn in a round if c=6, you entered and your rank was 5 among the entrants?

2. How much would you earn in a round if c=2, you entered and your rank was 4 among the entrants?

3. How much would you earn in a round if you decided not to enter the market?

4. How many rounds are there in total in this experiment?

Appendix C Auxiliary Tables and Figures

Table C1. Market capacity "c" values

Round	Session 1	Session 2	Session 3-6	Session 7 and 8
1	2	8	2	4
2	4	4	6	2
3	8	2	4	6
4	6	6	4	8
5	4	4	2	6
6	2	2	6	4
7	8	8	4	2
8	6	6	6	8
9	4	4	2	6
10	6	2	6	4
11	8	8	4	2
12	2	6	2	8

Table C2. Fixed effects logistic regression of the entry decision, sessions 3-8

	Selected demographics			All Demographics		
Variable	**Coefficient (Robust Std Err)**	**Marginal**	**z-statistic (p-value)**	**Coefficient (Robust Std Err)**	**Marginal**	**z-statistic (p-value)**
Intercept	-0.318		-1.11	0.079		0.14
	(0.288)		(0.268)	(0.546)		(0.885)
C	-0.055*	-0.012	-1.70	-0.036	-0.008	-1.07
	(0.032)		(0.089)	(0.033)		(0.286)
$E(\pi_{ijt})$	-0.002	-0.0001	-0.57	-0.005	-0.001	-1.07
	(0.004)		(0.570)	(0.004)		(0.286)
Skill	0.127	0.042	0.85	0.132	0.041	0.88
	(0.149)		(0.395)	0.149		(0.377)
ECON	-0.373***	-0.084	-3.78	-0.520***	-0.110	-4.58
	(0.100)		(0.001)	(0.114)		(0.001)
Self-selection	-0.919***	-0.050	-5.35	-1.172***	-0.085	-6.01
	(0.172)		(0.001)	(0.195)		(0.001)
Male	-0.204	0.126	-1.34	-0.231	0.130	-1.39
	(0.152)		(0.179)	(0.166)		(0.163)
Age				-0.081***	-0.017	-6.36
				(0.013)		(0.001)
Non New Zealander				-0.050	-0.010	-0.39
				(0.127)		(0.696)
Siblings				0.021	0.004	0.54
				(0.038)		(0.586)
Relative Income				-0.088	-0.019	-1.26
				(0.070)		(0.208)
City size				0.562***	0.118	9.28
				(0.060)		(0.001)
Living with others				0.030	0.006	0.94
				(0.032)		(0.348)
Money				0.000	0.0001	0.67
				(0.0001)		(0.502)
Finance study				0.0009	0.0002	0.61
				(0.002)		(0.542)
Rely				-0.034*	-0.007	-1.80
				(0.019)		(0.071)
Order	0.339***	0.076	3.66	0.445***	0.094	4.46
Random/Skill	(0.093)		(0.001)	(0.100)		(0.001)
Self-selection*Skill	0.091		0.49	0.102		0.54
	(0.186)		(0.625)	(0.189)		(0.592)
Self-selection*Male	1.187***		6.19	1.324***		5.91
	(0.192)		(0.001)	(0.224)		(0.001)
Round dummy	yes			yes		
Log-likelihood	-1418.1675	Pseudo R2= 0.0432		-1344.4625	Pseudo R2= 0.0929	

Sessions 3-8, n=2208, standard errors are not clustered at the session level because of a small number of sessions.
Run on StataSE 13.0. Robust standard errors used. Round 24 is the omitted control variable.
*, **, *** refer to statistical significance at the 10%, 5% and 1% levels, respectively.
Description of demographic variables: non New Zealander represents participants who are not from New Zealand; siblings represents number of siblings; relative income represents income far below avg, below avg, average, above avg or far above avg (from 1 to 5). City size, living with others, money, finance study and rely represent the size of the city from 2000 to 100 000+; number of people in a household, share of monthly expenses one finances alone; reliability of the data provided - 9 being most reliable.

Figure C1. Average forecasted and actual number of entrants in random-rank rounds and skill-rank rounds

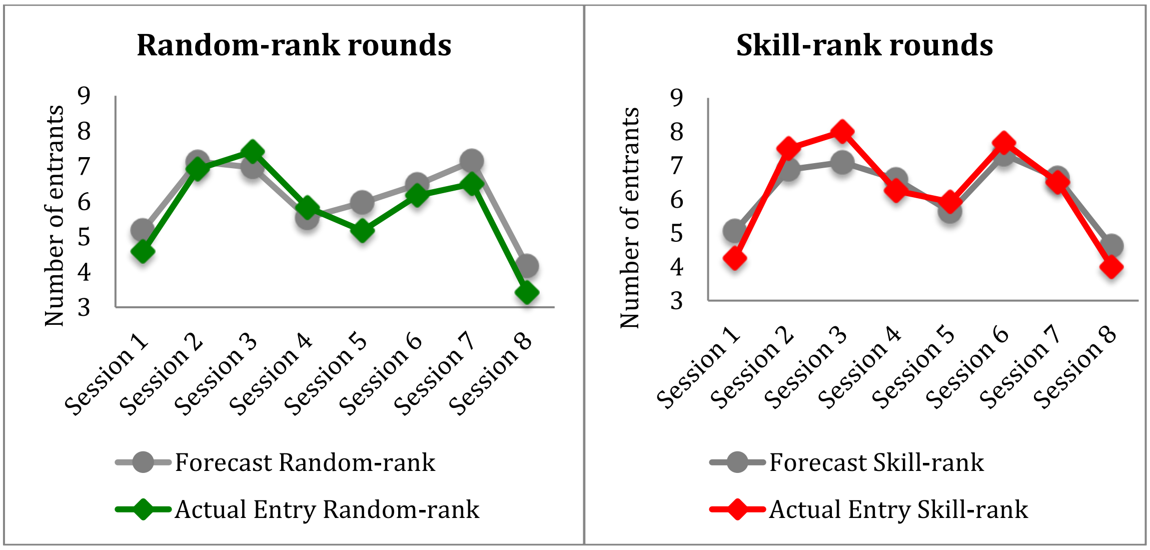


Figure C2. Matched-pair skill-random differential in number of entrants

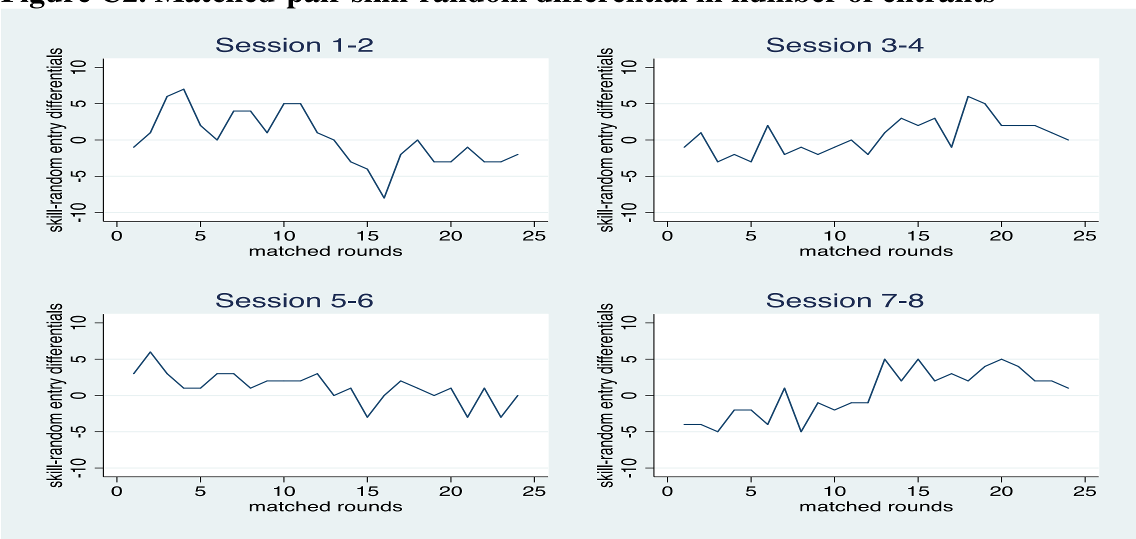


Figure C3. Averaged skill-random entry differential