ENTREPRENEURIAL FAILURE: STATISTICAL AND PSYCHOLOGICAL EXPLANATIONS

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Keywords:
Behavioral strategy, overconfidence, entrepreneurship, excess entry, decision making

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Entrepreneurial failure

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ABSTRACT

RESEARCH SUMMARY

Entrepreneurial start-ups suffer high rates of business failure. Previous research on entrepreneurial failure has focused on two kinds of explanations: statistical and psychological. Statistical explanations attribute excess entry to random errors made by boundedly-rational entrepreneurs attempting to estimate business opportunities in risky markets. Psychological explanations focus on entrepreneurial overconfidence and competition neglect. These explanations emerged independently and have not been tested or compared in the same study. In this experimental study, we distinguish entrepreneurial markets from other types of markets and test statistical and psychological hypotheses for all market types. We find that excess entry is significantly greater in small, risky markets than in other market types, and that confidence levels account for excess entry, over and above the effects of unbiased statistical errors.

MANAGERIAL SUMMARY

How can we explain the fact that most entrepreneurial ventures fail within five years? Market risk, inadequate capital and inexperienced management certainly play a role. However, from an economic point of view, it seems odd that inexperienced, under-funded people continue to engage in risky behavior that is widely known to fail. We conducted experiments that tested two explanations of entrepreneurial failure. The first explanation – the *statistical hypothesis* – argues that entrepreneurship involves high uncertainty, so random errors are inevitable and can produce excess entry (or under-entry). The second explanation – the *psychological hypothesis* – says that entrepreneurs' mistakes are not random but skewed heavily toward excess entry; hence, their decisions are distorted by psychological factors such as overconfidence. Our experiments found support for both of these explanations. Random errors under uncertainty explained 60% of the excess entry in our experiments. However, the overconfidence hypothesis correctly predicted that excess entry exceeds under-entry, and our psychological measures of overconfidence found support in the data. We also found that the markets that most often attract entrepreneurial investment – emerging markets with high uncertainty – were the markets most conducive to psychological overconfidence and excess entry. Hence, we conclude that potential entrepreneurs should pay less attention to their own abilities and aspirations, and more attention to the external realities of competition in the marketplace.

INTRODUCTION

Recent years have seen a resurgence of interest in the cognitive and behavioral origins of strategic management (Powell, Lovallo and Fox, 2011; Gavetti, 2012). Whereas mainstream research focuses on the economics of rent-seeking and competitive advantage, behavioral scholars emphasize the psychological and social micro-foundations of strategic behavior. According to Powell et al. (2011), “Behavioral strategy aims to bring realistic assumptions about human cognition, emotions, and social behavior to the strategic management of organizations and, thereby, to enrich strategy theory, empirical research, and real-world practice.” (p. 1371) If the pursuit of competitive advantage is inherently behavioral, as Levinthal (2011) argues, then psychologically-informed research will bring new insights to strategic management scholarship, while allowing the field to speak more effectively to practitioners.

Behavioral strategy also allows strategy researchers to use a wider range of research methodologies, including experimental methods, agent-based simulation, dynamic simulation, behavioral modelling and brain imaging (e.g., Laureiro-Martinez et al., 2014; Gary, Wood and Pillinger, 2012; Bartolet, Fox and Lovallo, 2011; Markle, 2011; Powell, 2011, 2014). As the behavioral trend continues, these methods will increasingly enable strategy scholars to apply cognitive and social psychology to theoretical and empirical anomalies in strategic management.

One such anomaly is excess market entry. Historical data show that more than half of entrepreneurial ventures fail within three years, and recent studies show no improvement in the long-term trend. Using data from the U.S. Census Bureau, Shane (2009, 2012) found that more than half of U.S. start-ups launched between 1977 and 2005 failed within five years, and that failure rates rose after 2000; recent data from Great Britain show that one-third of start-ups launched in the U.K. since 2000 failed within three years (Stout 2012); and in a study of 21 years of venture-funded market entry, Hall and Woodward (2010) concluded that “the reward to the entrepreneurs who provide the ideas and long hours of hard work in these startups is zero in almost three quarters of the outcomes.” (p. 1163) Interview data provide anecdotal support, showing that entrepreneurs often fail due to insufficient capital, inexperience, and failure to anticipate competitive moves (Ritholtz, 2012).

Research explanations for start-up failures focus on the problem of excess entry, and can be divided into two types: statistical and psychological. Statistical explanations hold that entrepreneurial market entry is inherently risky, and that some entrepreneurs will inevitably make poor entry decisions even if all decisions are correct on average (Hogarth and Karelaia, 2012; Harrison and March, 1984). Psychological explanations, meanwhile, argue that entrepreneurial market entry exceeds what random error would produce, and that excess entry can be explained by overconfidence. For example, Camerer and Lovallo (1999) found that too many players entered experimental markets when payoffs depended on skill, but not when payoffs were unrelated to skill; and Moore and colleagues (Moore, Oesch and Zietsma, 2007; Cain, Moore and Haran, 2013) attributed excess entry to a myopic focus on one's own abilities while neglecting the abilities of competitors.

Two problems remain unsolved in this research. First, existing studies have not shown whether differences exist between excess entry in entrepreneurial markets – that is, the small and risky markets that tend to attract entrepreneurial entry – and in larger or more stable markets; hence, it is possible that excess entry is not an entrepreneurial phenomenon but simply a feature of markets. Second, studies have not established whether entrepreneurial failure stems mainly from random errors under uncertainty (the statistical hypothesis), or requires explanations such as overconfidence, competition neglect and myopic self-focus (the psychological hypothesis).

We present findings from an experimental study designed to address these problems. We defined entrepreneurial markets as small markets in which market capacity is probabilistic rather than certain. We then compared excess entry in entrepreneurial markets with rates of entry in larger and more predictable markets. To test the statistical hypothesis, we computed theoretical rates of entry for decision makers making random errors under uncertainty, and compared these with actual rates of entry in our experimental markets. To test the psychological hypothesis, we developed a new measure of overconfidence and estimated regression models to examine the effects of confidence on market entry.

Overall, our results show that the statistical model with random errors explains 60% of excess entry, but that it does not fully explain observed patterns of over-entry and under-entry, especially the extreme excess entry found in the smallest and most volatile markets. Our regression analyses show that confidence adds significantly to the explanatory power of the model, and we conclude that entrepreneurial failure stems from a combination of statistical, psychological and market factors.

The following section reviews previous research and develops hypotheses. Subsequent sections describe the experimental design and empirical findings, and concluding sections discuss consequences for strategic management research and practice.

THEORETICAL BACKGROUND

New market entry is one of the most fundamental decisions in strategic management (Lieberman and Montgomery, 1988; Zajac and Bazerman, 1991). For entrepreneurs, market entry often entails reputational risk, unproven product or process technologies, and make or break financial commitments. For executives in established firms, market entry involves significant career risk, large resource commitments, and major reorientations of internal structure and culture. In market economies, new entry serves as a primary channel for technological and market innovation, and for bringing new waves of Schumpeterian creative destruction to the dynamics of industry competition.

Market entry has deep theoretical foundations in strategic management. Industrial economics began as an empirical challenge to economic assumptions of free market entry, and game theoretic models often focus on the competitive dynamics of market entry (Bain, 1956; Scherer, 1980; Fudenberg and Tirole, 1991). Fundamental concepts of market structure and industrial organization – market signalling, barriers to entry, excess capacity, economies of scale and scope – shaped the theoretical development of strategic management (Porter, 1980; Teece, 1980, 1984). At the core of strategy theory, the concept of competitive advantage rests on the assumption that firms can control market positions or resources that prevent rivals from competing away economic rents through market entry or expansion (Wernerfelt, 1984; Rumelt, 1984).

In perfectly competitive markets, theories in strategic management and economics predict that new firms will enter only if they can earn higher profits than they could earn from alternative employments of the same capital. New firms will enter if a market offers higher returns than other markets, and entry will continue until profits fall below the opportunity cost of capital – that is, when competition drives prices below the minimum average cost of production.

These assumptions have been tested extensively in experimental markets. For example, Kahneman and colleagues gave subjects a choice to enter markets with known capacity c and payoffs linked to the number of subjects who chose to enter; that is, subjects received positive payoffs if fewer than c players entered and negative payoffs if more than c players entered (see Kahneman, 1988). In repeated trials, subjects' collective entry decisions converged fairly quickly to market capacity c, even without explicit coordination or collusion. Subsequent studies extended these results to experimental markets with more players, larger payoffs, probabilistic payoffs, and other conditions (e.g., Sundali, Rapoport and Seale, 1995; Rapoport et al., 1998).

These findings show that experimental markets can replicate the expected dynamics of competitive market entry. However, they do not explain the rates of excess entry we actually observe, especially in entrepreneurial markets. If no entry barriers are present, and a market offers higher returns than other opportunities, then entrepreneurs should enter; otherwise, they should not. Some potential entrants will hold false beliefs about market conditions or the intentions of other entrepreneurs, and thus will enter when they should not – but these errors should rectify themselves fairly quickly, as in the Kahneman experiments. We should not observe that half of entrepreneurs fail within five years, or that entrepreneurs continue failing at the same rate for decades even when entrepreneurial mortality rates are widely known. These facts suggest two possibilities: an impediment in the relevant markets for information, or a behavioral anomaly in the choices of entrepreneurs.

These considerations gave rise to the statistical and psychological explanations for excess entry. Statistical explanations claim that entrepreneurial activity is inherently risky and subject to incomplete information; hence, entrepreneurs' entry decisions are subject to random errors, some of which produce excess entry. Psychological explanations claim that entrepreneurs focus excessively on their own abilities while neglecting the strengths of competitors; hence, entrepreneurs' errors are not random but biased systematically toward overconfidence, leading to more excess entry (and less under-entry) than can be attributed to random error. The next section examines these explanations and develops hypotheses for empirical testing.

HYPOTHESIS DEVELOPMENT

Entrepreneurial activity involves the pursuit of new business opportunities in nascent markets with uncertain growth prospects. Hence, our first hypothesis compares excess entry in these markets with rates of entry in larger and more stable markets.

Why should small markets induce more excess entry? The answer can be statistical or psychological. In a small market, one or two entrants can produce significant proportional increases in excess capacity, whereas the same number of entrants may have negligible proportional effects in larger markets. The psychological hypothesis argues that decision makers pay too much attention to their own abilities (myopic self-focus) and too little attention to external factors such as market size, market volatility and the abilities of other players (e.g., Zajac and Bazerman, 1991; Moore, et al., 2007; Cain, et al., 2013). At the limit, if players completely ignored market size, they would enter markets of all sizes at the same rate, which implies over-entry in small markets and under-entry in large ones. The actual effect is not this extreme, but psychological phenomena could induce this tendency.

There is some evidence that small markets induce more excess entry than large markets. In a series of entry experiments designed to test market equilibria, Camerer, Ho and Chong (2004) found that subjects tended to over-enter small markets and under-enter large markets, even in the absence of skill-based payoffs. In a 16-player game with skill-based payoffs, Bolger, Pulford and Colman (2008) found excess entry of 30% in games with market capacity of eight players, and 110% in games with market capacity of four players. These findings suggest that market size plays a role in excess entry, and entrepreneurial markets may attract more excess entry than larger markets.

There is little evidence on whether market risk induces excess entry, and no clear results on whether the interaction of market size and market risk plays a role in excess entry. Wu and Knott (2006) argued that entrepreneurs distinguish between two uncertainties – uncertainty in their own skills and uncertainty in market demand – and are risk-seeking with respect to their own skills but risk-averse with respect to market uncertainty. The joint effects of these propensities are unclear, but if entrepreneurs are risk-averse with respect to market volatility, then excess entry in entrepreneurial markets would more likely stem from overconfidence than market uncertainty. The authors found support for these arguments in a field study of start-ups in commercial banking, concluding that "entrepreneurs as a group appear to be both risk averse and overconfident." (p. 1328)

Based on these arguments, our first hypothesis posits that excess entry is greater in entrepreneurial markets – that is, small markets with uncertain capacity – than in larger and more stable markets:

H1: Entrepreneurial markets attract more excess entry than other market types.

Statistical explanations of excess entry hold that the essential fact about market entry is uncertainty. Entrepreneurs face incomplete information about market capacity, their own relative abilities, and the entry intentions of other players. Market entry decisions are based on forecasts and fallible judgments, and even the most informed judgments are subject to error. Unbiased errors produce random dispersion around a zero mean, and statistical explanations argue that random errors can produce a collective outcome of excess entry (or under-entry), in the same way that a series of coin tosses can produce more heads than tails. When excess entry happens, it is tempting to diagnose "overconfidence" even when excess entry stems entirely from a random process. Harrison and March (1984) referred to this phenomenon as "post-decision surprise" – that is, an apparent pattern caused by the statistical structure of the decision problem.

Hogarth and Karelaia (2012) developed a model in which an entrepreneur makes an estimate x of a business opportunity, the true value of which is y. The estimate is $x = y + e$, where e is a normally distributed error term $N(\mu_e,\sigma_e)$.

Unless $\sigma_e = 0$, entrepreneurs will commit errors in forecasting the true value of the opportunity, so the correlation between forecasted and realized returns will be less than 1. Even if $\mu_e = 0$ (judgments are correct on average), random errors will produce successes and failures, lucky guesses and unlucky guesses. Hogarth and Karelaia (2012) conducted simulations for different values of μ_e and σ_e. Their results showed that, even when market participants made well-calibrated estimates on average ($\mu_e = 0$), simulated markets sometimes exhibited excess entry, and excess entry went up as market assessments became noisier (that is, as σ_e increased). Entrants became more susceptible to post-entry failure if their forecasting errors happened to fall on the side of over-estimating market demand, which gave an illusion of psychological overconfidence. But according to the authors, it would be wrong to call this "overconfidence," since the simulated agents behaved randomly and without bias ($\mu_e = 0$), their errors driven entirely by a random process rather than psychology.

These considerations lead to the following hypothesis:

H2: Unbiased statistical errors explain a significant proportion of excess entry in entrepreneurial markets.

Psychological explanations take a different approach, arguing that new market entry does not follow a random process but is biased systematically to produce more excess entry (and less under-entry) than in an unbiased random model. Even if excess entry derives partially from market uncertainty, as in the Hogarth and Karelaia models, they claim that empirical patterns of market entry do not follow the predictions of unbiased simulations. In terms of the Hogarth and Karelaia model, psychological explanations claim that $\mu_e > 0$ – that is, new entrants have positive decision biases that produce too little under-entry and much over-entry compared to unbiased statistical models.

Previous experimental studies support this view. In market entry experiments by Kahneman and colleagues, subjects' payoffs depended on how many people entered the market: if too few subjects entered, all entrants made money; if too many subjects entered, all entrants lost money. Camerer and Lovallo (1999) conducted similar experiments, but created a skill-based condition in which subjects' payoffs were determined by rank-ordered scores on an experimental task (a trivia quiz). In these experiments, with market capacity *c* known to subjects in advance, only the *c* highest-ranked entrants made money, and all other entrants lost money; hence, subjects were incentivized to form beliefs about their (unknown) ranks on the experimental task.

The authors found that skill-based competition induced more players to enter the market, leading to excess entry and losses on average (-$1.56) for market entrants. When subjects were allowed to self-select into skill-based competition, excess entry was even greater and subjects incurred larger losses on average (-$13.13). Subjects in a control group with payoffs based on random ranks rather than skill-based ranks behaved similarly to subjects in Kahneman's experiments, converging to market capacity and earning profits (+$16.87) in an average round. Hence, the authors argued that skill-based competition induced players to focus myopically on their own abilities, neglect the abilities of competitors, and make overconfident entry decisions.

Subsequent studies introduced refinements to the Lovallo-Camerer paradigm. Moore, Oesch, and Zietsma (2007) varied the difficulty of the experimental task and found that simple tasks induced more entry than difficult tasks, yielding overconfidence in the simple task and underconfidence in the difficult task. They also found that entry did not vary significantly in markets of two sizes (3 and 4). The authors attributed these findings to egocentric bias in market entry decisions – namely, the tendency to focus on one's own abilities to the exclusion of nearly everything else, including the fact that an easy task is easy for everyone (and a hard task is hard for everyone), and that larger markets can accommodate more people. Hence, "entrepreneurs tend to overweight personal factors and underweight consideration of the competition when making venturing decisions, suggesting that market-entry decisions are indeed driven by simple-minded logic." (Moore et al., p. 452)

In a further study of task difficulty, Cain, Moore, and Haran (2013) distinguished between three types of overconfidence, which they referred to as overplacement (believing that one's performance ranking is above average), overestimation (excessive optimism in forecasting future outcomes), and overprecision (over-belief in the accuracy of one's estimates). Combining laboratory experiments with a field study, the authors concluded that excess entry stems more from overplacement than other causes, but not always from competition neglect – that is, not from neglecting the competition entirely but from underestimating competitors' abilities in relation to one's own.

Entrepreneurial market entry involves skill-based competition and uncertainty about the relative abilities and entry intentions of other players. In these conditions, the overconfidence hypothesis predicts that entrepreneurs will commit systematic rather than random errors, and that the systematic errors derive from entrepreneurial overconfidence. Thus, we hypothesize as follows:

H3: New entry in entrepreneurial markets is systematically biased toward excess entry (and away from under-entry), and the bias is explained by entrepreneurial overconfidence.

Market entry is one of the most crucial decisions in strategic management, and excess entry in entrepreneurial markets remains an empirical anomaly. Experimental studies have not established that entrepreneurial markets attract more excess entry than other market types (H1), nor whether the statistical hypothesis (H2) or psychological hypothesis (H3) better explains actual patterns of new market entry. Our experiments were designed to address these issues.

EXPERIMENTAL DESIGN

We based our market entry experiments on the design of Camerer and Lovallo (1999). In their experiments, subjects were given the choice to enter markets of various sizes or market capacities (c), and payoffs were determined by their ranked performance on a trivia quiz (on sports or current events). In any game in which the number of entrants exceeded c, all entrants ranked worse than c lost money; for example, if c=2, the first-ranked entrant made $33, the second-ranked entrant made $17, and every other entrant lost $10 (the experimenters staked them to a small amount of money).

Our procedure was as follows:

1. Using an experimental database (ORSEE, Greiner, 2004), we recruited subjects to play a game in which payoffs depended on their performance in a general knowledge quiz. Subjects were seated randomly at computer desks in an experimental laboratory of the School of Business and Economics of a prominent European university. Subjects had no communication or visual contact with each other. The experiment was computerized using z-Tree (Fischbacher, 2007), and instructions were displayed on computer monitors. None of the subjects had prior experience in a market entry experiment.

2. Upon arrival, subjects were given a stake of €12. In the first part of the experiment, subjects completed a general knowledge quiz consisting of 14 binary choice questions. At this stage, subjects received no feedback on their performance (on average, people answered 8.0 out of 14 questions correctly, *SD* = 2.05).

3. Subjects were given general instructions and a comprehension test to ensure their understanding of the market entry game (instructions available from the authors). Subjects were told that they would play ten rounds of the game against six other players (seven players including the subject), deciding in each round whether or not to enter a market. Payoffs in any round would be determined by their performance on the quiz, and by market capacity c in that round. Subjects were told that their payoffs would be determined at the end of all rounds by their performance in one randomly-chosen round.

4. In each session, 14 players were randomly assigned to two groups of seven, and randomly reassigned to new groups of seven after each round. To avoid learning effects, no feedback was given about the number of entrants or payoffs of any player.

5. Market size c varied from round to round. In each round, the c "best" entrants (based on quiz scores) received payoffs of €7.50; all further entrants lost €10. In any round, the leading c players made €7.50, and the market was in equilibrium when $m = 1.75c$ players entered the game. If more than $1.75c$ players entered, total industry profits were negative; if fewer entered, total industry profits were positive (complete analysis of the Nash equilibrium is available from the authors).

6. In half the sessions, players were confronted with known market capacities (c); in the other half, market capacities were subject to risk. In the "known" condition, c was either 1, 2, 3, 4, or 5; in the "risky" condition, c had expected values of 1, 2, 3, 4, or 5, with realized values uniformly distributed across three outcomes, as follows: (0,1,2), (1,2,3), (1,3,5), (2,4,6), or (3,5,7). In all rounds, players knew the condition they were playing,

and, in the risky condition, the distribution of possible market capacities. All conditions and payoffs are shown in Table 1.

– INSERT TABLE 1 HERE –

7. After completing the first block of five rounds, subjects played a second block of five rounds. Before the second block, subjects were given partial information about their true ranks on the trivia quiz. Half of subjects (Group A) were told their own number of correct answers on the quiz (but not the distribution of correct answers or their rank); the other half (Group B) were given the distribution of correct answers for all players (but not their own score). Data from these rounds were used to test the overconfidence effect, as described in the next section.

8. A total of 112 participants took part in the experiment: 50 were male (45%), 62 were female (55%). Each subject played ten games and made ten decisions (five in each block), for a total of 1,120 decisions (560 decisions in each block). In practice, 14 participants took part in each session, randomly assigned to two groups of seven. Eight experimental sessions were run altogether (8 sessions x 14 subjects per session = 112 subjects), and there were 160 games (80 in the first block, 80 in the second).

9. After the market entry game, we elicited subjects' beliefs about the number of entrants in each condition. For correct answers, subjects received a small additional payoff. We also gathered demographic information and measured risk attitudes using a lottery choice task

(Holt and Laury, 2002).[1] A random device determined which round was used to compute payoffs, and payments were made privately.

A brief summary of the research design is given in Table 2. The design differed from the Camerer and Lovallo experiments in three important respects: first, we added markets of uncertain capacity; second, we minimized learning effects by withholding previous results and reassigning players randomly between rounds; and third, we controlled for biases related to ambiguity aversion and betting on future events (Heath and Tversky, 1991; Fox and Tversky, 1995; Rothbart and Snyder, 1970) by having our subjects take the quiz before the experiment. These changes allowed us to distinguish markets by size (market capacity) and volatility (known and risky), and to conduct controlled tests of our three hypotheses.

– INSERT TABLE 2 HERE –

RESULTS

Excess Entry

H1 posited that entrepreneurial markets attract excess entry. Figure 1 shows results for the four most extreme market types in the first block of experiments (N = 112 subjects; 560 entry decisions). The figure shows the percentage of excess entry or under-entry relative to market capacity c, and average profit per round for entrants in each market.

– INSERT FIGURE 1 HERE –

[1] In the Holt and Laury (2002) task, subjects are asked to make ten choices between a set of paired lotteries, one more risky than the other. In the first choice, the probability of the risky option with higher payoff is 1/10; in the second choice, the probability is 2/10, and so on. When the probability reaches 4/10, the expected payoff of the risky option equals the expected payoff for the less risky option; when the probability is 5/10 or higher, the expected payoff of the risky option is greater. A risk-neutral person will switch from one to the other at p = 5/10. The later the subjects' switching-points, the greater their risk aversion.

As shown in Figure 1, the number of entrants in the smallest risky market was 3.5 times greater than what could be accommodated by market capacity, and the average round produced a loss of €17.50 for market entrants. This compares with slight excess entry in the smallest stable market (and a slight loss for entrants), and under-entry in both the largest stable market and the largest risky market, both of which produced profits for market entrants. In statistical tests, the ratio of actual to efficient entry was significantly greater in the smallest risky market than in the other three markets ($p < .001$), and average profits were significantly lower ($p < .001$).

Table 3 shows complete results for markets of all sizes and volatilities in the first block of experimental rounds. Table 3 gives the ratio of entrants to known or expected market capacity *c*, the ratio of entrants to the zero-profit industry equilibrium, and the average profit per round earned by entrants in each market.

– INSERT TABLE 3 HERE –

Table 3 shows that overall rates of entry did not depend on market volatility, consistent with the findings of Wu and Knott (2006): subjects on the whole were risk-neutral, with $R(c) = 1.36$ in both the known and risky conditions. Moreover, entry was not excessive in relation to market equilibrium: the average round attracted 36% more entrants than could be accommodated by market capacity *c*, but fewer entrants than needed to reach the zero-profit equilibrium. Hence, 36% of entrants lost money, but entrants made a profit on average (the experimental rounds produced an average profit of €11.75).

As further tests of H1, we compared excess entry in the smallest risky market – the market with capacity $c = (0,1,2)$ – to entry in all other markets. The results show that this market attracted a significantly higher proportion of excess entry than any other market we studied. The smallest risky market attracted twice as many entrants as the zero-profit equilibrium, and was one of only three markets that lost money on average: one market lost €1.26, another lost €6.23, and the entrepreneurial market lost €17.50. The average number of entrants in the entrepreneurial market on average (3.50) was not much smaller than the 4.00 entrants who entered the market with c = (3,5,7), suggesting considerable coordination failure and inefficient market outcomes.

This can be seen more clearly in Figure 2, which compares the mean number of entrants for known and risky demand for all market sizes. In markets with known demand, the number of entrants is roughly linear in market capacity, varying around a mean that exceeds market capacity by 36%. This entry pattern is largely in line with equilibrium predictions. For the risky condition, average entry also exceeds market capacity by 36% but the relationship between the mean number of entrants and demand is s-shaped: when expected capacity is lowest, people over-enter the market and more than 70% of entrants lose money; when expected capacity is highest (the 3,5,7 condition), people under-enter the market and profit opportunities are lost. The average number of entrants is identical for the known and risky conditions, but the interaction effect reveals significant differences in the dynamics of market entry.

– INSERT FIGURE 2 HERE –

The Statistical Hypothesis

H2 posited that random statistical errors explain a significant proportion of observed excess entry. To test this hypothesis, we developed a statistical null model of our experimental markets.

Following Hogarth and Karelaia (2012), we assumed that subjects based their entry decisions on unbiased judgments. In the experimental markets with known capacity, subjects knew the number of players (seven) and market capacity (one to five), but not their rank-orderings on the quiz or the entry intentions of other players. As a statistical model of the decision, we assumed that subjects had correct beliefs on average about their rank-orderings on the quiz and entry decisions of other subjects. For a given player facing a market with capacity *c*, this implied entering the market with probability *c*/7. For example, if the market was known to support two entrants, the entry probability for a given player was 2/7, and the expected number of entrants would follow a binomial probability model with $n = 7$ and $p = 2/7$.

Table 4 illustrates the binomial model for c=2. As shown in the table, the probability of observing exactly two entrants is .32, the probability of under-entry (zero or one entrant) is .36, and the probability of over-entry (more than two entrants) is .32. Hence, when c=2, fallible judgment under uncertainty is sufficient to produce excess entry in 32% of games.

– INSERT TABLE 4 HERE –

In the experimental markets with uncertain capacity, we computed the binomial model by averaging the probabilities of the three possible market capacities. For example, in market condition (1,3,5), market capacities 1, 3 and 5 were equally probable; hence, an unbiased player would compute the mean of the probabilities of realizing one entrant in certainty condition c=1 (p=.055), three entrants in certainty condition c=3 (p=.294), and five entrants in certainty condition c=5 (p=.085) – which yields p =.145. As expected, market uncertainty increases the decision-maker's dispersion of errors; for example, the probability of excess entry when expected capacity is three (condition 1,3,5) is .42, but in certainty condition c=3 is .35.

Table 5 shows the binomial probabilities of realizing each number of entrants in all of our experimental markets. Table 5a shows entry probabilities for games with certain capacity; Table

5b shows probabilities for games with uncertain capacity; Table 5c shows combined results for both conditions.

– INSERT TABLES 5a, 5b and 5c HERE –

As shown in Table 5, the binomial model predicts that excess entry will occur in 33.0% of games with known market capacity, 39.2% in games with unknown capacity, and 36.1% of overall games. The model predicts that the correct number of players will enter – for example, that three players will enter when market capacity is three – in 32.4% of games with known capacity, 18.0% of games with unknown capacity, and 25.2% overall.

As a test of the statistical hypothesis, Table 6 shows the entry decisions of subjects in all experimental conditions, and compares them with the binomial predictions in Table 5. The results show that the binomial model accurately predicts the proportion of games in which the correct number of players will enter: the correct number of players entered in 27.5% of games with known market capacity (compared with 32.4% in the binomial model), 20.0% of games with unknown capacity (compared with 18.0%), and 23.7% overall (compared with 25.2%).

– INSERT TABLES 6a, 6b and 6c HERE –

On the other hand, the binomial model significantly underestimates the actual degree of excess entry, predicting excess entry in 36.1% of all markets compared with 60.0% in the actual data (p<.001); hence, the model explains 60.2% of excess entry in the experimental markets (.361/.600). The statistical model performed better when market capacity was unknown, explaining 68.2% of excess entry when capacity was unknown (.392/.575), compared with 52.8% when capacity was known (.330/.625).

The binomial model significantly over-estimated the degree of under-entry in the data, predicting under-entry in 38.7% of all games compared with 16.2% in the actual data (p<.001). Again, the statistical model performed slightly better when market capacity was unknown rather than known, but in both conditions significantly over-estimated the incidence of under-entry.

The statistical model was not disconfirmed in every condition. Of the ten market conditions in Tables 6a and 6b (five with known c, five with unknown c), over-entry significantly exceeded expectations in four of ten conditions, and under-entry was significantly less than expectations in five of ten conditions. In five of the twenty comparisons, the signs were not in the directions predicted by the overconfidence hypothesis. What the statistical model failed to explain was the extreme excess entry observed in some markets (including the smallest risky market) and the significant aggregate effects of excess entry in markets with known c, markets with unknown c, and markets as a whole. Overall, as summarized in Figure 3, the results suggest that the errors committed by market entrants were systematic rather than statistically unbiased.

– INSERT FIGURE 3 HERE –

The Overconfidence Hypothesis

The overconfidence hypothesis makes two claims: that entry decisions are not random but biased toward excess entry, and that excess entry can be explained by overconfidence. The previous analysis supports a hypothesis of biased entry decisions but does not prove overconfidence. As a test of the overconfidence hypothesis, we developed a new measure of confidence and tested its effects in a regression model.

We computed confidence levels for each subject by comparing entry decisions in the second block of experimental rounds to entry decisions in the first block. Recall that in the second block, subjects received partial information about their ranks: half of subjects (Group A) learned their own number of correct answers on the quiz (but not the overall distribution), and the other half (Group B) learned the distribution of correct answers for all players (but not their own). Comparing subjects' decisions in the two blocks allowed us to measure how much overconfidence (or underconfidence) subjects had exhibited in the first block of entry decisions. Specifically: less aggressive entry in the second block gave evidence that a subject held overconfident beliefs about their abilities during the first block of decisions; more aggressive entry decisions in the second block gave evidence that a subject held underconfident beliefs during the first block; and no significant differences in entry decisions between the two blocks gave evidence of well-calibrated beliefs.

In sum, we defined overconfidence (or underconfidence) as the positive (or negative) difference between a subject's decisions to enter in the first block as compared to the second. We then examined results from the first block to determine whether overconfidence explained a significant proportion of excess entry. To test these effects, we estimated logit models that employed subject-specific random effects to control for unobserved heterogeneity.

Before discussing the logit models, we note that 34.8% of subjects made less aggressive entry decisions in the second block of experiments, and were therefore overconfident; 23.2% of subjects made more aggressive entry decisions in the second block, and were therefore underconfident; and 42.0% of subjects did not change the overall aggressiveness of their entry decisions, and were well-calibrated. Hence, the raw data suggest that subjects were skewed toward overconfidence.

Our logit models used entry as the dependent variable and introduced control variables before testing the relationship between confidence levels and market entry. We defined *entry* as a binary variable, coded 1 for entry and 0 for non-entry. The independent variable *size* represented the known or expected market capacity *c*. *Market volatility* was coded 1 for risky markets and 0 for known markets. The variable *rank* represented the subject's rank on the trivia quiz. *Confidence* represented the difference between entry choices in the first and second blocks of experiments, with a positive value indicating overconfidence and a negative value indicating underconfidence.

We also included measures of risk aversion and subjects' beliefs about the number of entrants. *Risk aversion* was measured as the subjects' switching points in the lottery choice task by Holt and Laury (2002) (see footnote 1); *belief* represented subjects' beliefs about how many people would enter each market; and *gender* was coded 1 for male participants and 0 for females. A zero-order correlation matrix for all variables is shown in Table 7.

– INSERT TABLE 7 HERE –

Three logit models were estimated for entry in the first five rounds (the first block). In all three models, the dependent variable was *entry*. Model 1 examined the effects of *market size* and *market volatility*, and the *size*volatility* interaction, on the decision to enter. Model 2 added *rank*, *confidence* and *risk aversion*; and Model 3 added *belief* and *gender*. Table 8 gives the logit results for all three models, which combines the analysis for groups A and B (separate analyses did not reveal significant between-group differences – analyses available from the authors).

– INSERT TABLE 8 HERE –

Results for Model 1 show, as expected, that subjects were more likely to enter large markets than small markets, and more likely to enter risky markets than known markets. The negative interaction effect (*size*volatility*) shows that the "risky market" effect is attributable to excess entry in small risky markets, i.e., entrepreneurial markets.

Model 2 shows the main effects of rank and confidence when market size and volatility are held constant. The significant coefficient for *rank* shows, as expected, that the better the subject's rank on the quiz, the more likely the subject was to enter a market. The coefficient for *confidence* is positive and significant, showing that subjects' entry decisions were influenced by their degree of confidence in their own abilities. As expected, *risk aversion* correlated negatively with the decision to enter.

Overall, the data provide support for the overconfidence hypothesis. Model 2 shows a positive and significant coefficient for *confidence* ($p<.001$) when controlling for *market size*, *market volatility, rank* and *risk aversion*; and Model 3 shows a positive and significant coefficient for *confidence* ($p<.001$) when controlling for gender and players' beliefs about the entry intentions of other players. As further tests, we ran regressions using transformations of the confidence variable (confidence^2 and confidence^3) but these did not yield significant results, suggesting a degree of linearity in the confidence effect on excess entry. We also ran separate regressions for the variables *overconfidence* and *underconfidence* (analysis available from the authors), which produced a significant coefficient for overconfidence ($p=.01$) and a non-significant coefficient for underconfidence ($p=.16$). This suggests that the confidence effect is driven more by the overconfidence of excess entrants than by the underconfidence of under-entrants.

As noted earlier, we elicited subjects' beliefs about the entry intentions of other players in each market. In all markets, subjects' expectations about rates of entry adhered closely to market capacity c, suggesting that subjects expected tacit coordination with other subjects and held accurate beliefs about *c* in the various markets (analysis available from the authors). Thus, excess entry cannot be assigned to false beliefs about the number of entrants the market will support.

Model 3 shows that gender had a significant effect on entry, with men more likely to enter than women, even after controlling for risk aversion, confidence, ranks, and beliefs. This is consistent with previous studies on gender and overconfidence (e.g., Niederle and Vesterlund, 2007; Barber and Odean, 2001). We conducted separate analyses for male and female subsamples, which produced no significant differences in our hypothesis tests. For both genders, entrepreneurial markets had significant rates of excess entry, significantly more excess entry than in other markets, and highly significant regression coefficients for the variables *volatility*, *size*volatility* and *confidence* (analysis available from the authors).

DISCUSSION AND CONCLUSIONS

Market entry is a central phenomenon in strategic management theory and practice (Lieberman and Montgomery, 1988; Meyer et al, 2009). The overconfidence hypothesis argues that people facing market entry decisions tend to focus on their own abilities while neglecting the contingent moves of competitors (Kahneman and Lovallo, 1993; Zajac and Bazerman, 1991; Simonsohn, 2010). In real-life markets, this can occur even among large firms competing in global industries. For example, in the dry bulk cargo shipping industry, an economic boom led to over-investment and declining returns on average, as decision makers failed to anticipate that their rivals would also expand capacity during economic booms (Greenwood and Hanson, 2013).

Our research studied the impacts of fallible judgment and overconfidence on market entry. Previous studies had shown the effects of overconfidence on excess entry in skill-based competition, along with the moderating effects of market size and task difficulty (Camerer and Lovallo, 1999; Moore, et al., 2007; Cain, et al., 2013; Bolger, et al., 2008; Wu and Knott, 2006).

We aimed to contribute to this research in two ways. First, we sought to establish whether excess market entry occurs disproportionately in entrepreneurial markets – small markets with risky demand – as compared with other market types. Second, we sought to establish whether unbiased errors due to fallible judgment could explain observed patterns of entry when tested alongside a theory of overconfidence (Hogarth and Karelia, 2012; Harrison and March, 1984).

Our results show that entrepreneurial markets attract more excess entry than other markets. Whereas the number of entrants in the average market exceeded market capacity by 36%, entry in the smallest risky market exceeded market capacity by 250%; and whereas seven of ten market types earned profits, with overall profits averaging €11, the smallest risky market lost €17 on average. These findings reflected a combination of main and interaction effects. Small markets attracted more excess entry than large markets on average, but overall entry rates did not differ between markets with known and uncertain capacity (before controlling for market size). Neither main effect (size or volatility) influenced excess entry as much as the interaction of small market size and uncertain capacity that defines the entrepreneurial market.

Why do entrepreneurial markets attract so much excess entry? The results suggest that the causes are both statistical and psychological. The unbiased statistical model accurately predicted the rate of correct market entry (predicting correct entry in 25.2% of games, compared with 23.7% in the data), and explained 68% of excess entry in risky markets and 60% of excess entry overall. These findings suggest a significant role for random statistical noise in explaining excess entry, an effect largely ignored in prior research on overconfidence.

On the other hand, the statistical model did not predict the systematic bias toward excess entry or the deficit of under-entry. Among participants who were overconfident or underconfident, the former exceeded the latter by half, suggesting a general tendency to overconfidence. In regression models controlling for many forms of statistical uncertainty – including ranks, market capacity, and beliefs about the number of entrants – confidence explained significant variability in market entry, and overconfidence had a larger effect than underconfidence. Overall, the results suggest that overconfidence plays a significant role in excess market entry.

We believe our measure of confidence represents a novel contribution to research on overconfidence. Unlike previous measures, which inferred overconfidence directly from the tendency to enter markets, we measured confidence as the difference between players' entry decisions when uninformed about their relative abilities, and their entry decisions when partially informed about their relative abilities. We believe this measure corresponds closely with the psychological construct of overconfidence – that is, construing information to support an over-belief in one's prospects for success – and captures key aspects of overconfidence that drive excess entry, such as "overplacing" one's abilities in relation to competitors (Cain et al., 2013).

Along with Cain et al. (2013), ours is one of the few studies of market entry to employ a majority sample of female subjects. Males are more inclined to both overconfidence and excess entry, and an all-male sample would have produced larger effects. Nonetheless, our results show the robustness of excess entry and the overconfidence hypothesis: for males and females alike, excess entry was significantly greater in entrepreneurial markets than in other market types.

We acknowledge several limitations of our study. First, although we draw conclusions about entrepreneurial markets, we did not study the traits of real-world entrepreneurs – for example, whether entrepreneurs are more or less susceptible to overconfidence than the general population (e.g., Busenitz, 1999). Moreover, by not giving feedback to subjects between rounds, we foreclosed entrepreneurial learning from multiple trials (as in serial entrepreneurship).

Withholding feedback allowed us to control for learning effects, but our results may overestimate market inefficiency and coordination failure in markets where learning does occur.

In various ways, we may have mis-estimated the relative strengths of the statistical and overconfidence hypotheses. For example, if players' entry probabilities in the statistical model were linked to the zero-profit equilibrium rather than market capacity, the model's overall predictions would improve. In the market with c=2, the zero-profit equilibrium is 3.5 entrants, and we could construct a binomial model in which players enter with probability .50 (3.5/7) rather than .29 (2/7). If applied to all markets, this model would make better predictions overall and obviate the need for psychological explanations in some markets. On the other hand, our data on players' beliefs showed that the expected number of entrants adhered closely to market capacity (analysis available from the authors). This suggests that the zero-profit equilibrium was not a salient reference point for players, and that a model linked to market capacity ($p = c/7$) was most appropriate for these markets.

It is also possible that we under- or over-estimated the overconfidence effect. For example, entrants in real-world markets use their own expertise, training and experience to self-select into a specialized field. In our experimental markets, entry decisions were not based on self-selection into a skill condition or on skills the participants prepared in advance, but on performance in a general knowledge quiz. To the extent that real-world markets involve self-selecting specialists, our study may have underestimated the overconfidence effect.

We may also have mis-estimated the overconfidence effect by partially endogenizing the confidence variable in the logit models – that is, by using the difference in entry in two conditions to predict entry in one of the conditions. It is true that a subject who entered aggressively in the first block of experiments is more likely to reduce entry in the second block of experiments. On the other hand, subjects could not “learn” in our experiments, and thus had no basis for changing prior behavior except for the newly-provided information about their true abilities. Thus, we believe the measure of overconfidence is reliable and robust.

Our results have potential consequences for market entry decisions in strategic management practice. In particular, our results show that fallible judgment and overconfidence operate differently depending on market conditions. In contemplating new market entry, managers should consider not only the size and volatility of markets, but also the effects of market size and volatility on statistical errors and overconfidence bias. Small markets are less prone to statistical errors by an unbiased decision maker – for example, the binomial model predicted excess entry in 28.2% of games when c=1 compared with 41.2% when c=5 – and yet small markets were slightly *more* prone to excess entry by overconfidence (actual excess entry in 68.7% of games when c=1 and 62.5% when c=5). Similarly, markets with known capacity are less prone to statistical errors than markets with unknown capacity (the binomial model predicted 33.0% excess entry in stable markets and 39.2% excess entry in volatile markets), yet markets with known and unknown capacities produced similar degrees of excess entry (before controlling for market size). The key message for decision makers is that the combination of small market size and high market volatility is conducive to psychological biases that produce judgmental errors.

Can managers make better entry decisions? From an evolutionary point of view, traits such as myopic self-focus and overconfidence emerged as adaptations to promote survival and reproduction among our human ancestors. They are socially and biologically embedded and resistant to psychological remedies at the level of the individual (Zac and Denzau, 2001). At the same time, entrepreneurs and organizations can employ structured tools and decision processes to minimize errors in market entry decisions (Heath, Larrick and Klayman, 1998; Thaler and

Sunstein, 2008). These include similarity-based forecasting, in which entry decisions are compared to a reference class of analogous past decisions (Lovallo, Clarke and Camerer, 2012); dynamic simulation, modelling causal relationships among key success factors (Sterman, 2000); and scenario analysis, in which decision makers evaluate a range of alternative futures and contingent moves of other firms (Goodwin and Wright, 2001). Strategy scholars and practitioners can build awareness of overconfidence and related biases by promoting tools that produce more robust market entry decisions.

Market entry is a fundamental issue in strategic management, and excess entry in entrepreneurial and other markets is a long-standing empirical anomaly. Where past studies established a broad tendency to excess entry, we find a disproportionate tendency to excess entry in entrepreneurial markets, and a combination of statistical and psychological effects that explain observed entry patterns. We believe these results contribute to the growing field of behavioral strategy by advancing the debate on overconfidence and excess entry, and by suggesting ways in which strategists can improve firm performance through more effective decision making.

ACKNOWLEDGEMENTS

The authors are grateful for the editorial support of Steven Floyd and for the helpful comments of two anonymous reviewers. We also thank Colin Camerer, Jerker Denrell, Philipp Koellinger, and Christian D. Schade for their helpful comments, along with participants in presentations at the Academy of Management, the SPUDM, the Verein für Socialpolitik, and the Research Seminar at Warwick Business School. This project received financial support from VolkswagenStiftung and the Oxford Entrepreneurship Centre, which is gratefully acknowledged.

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TABLES AND FIGURES

Table 1: Payoffs by Market Capacity and Type (in Euros)

	Actual or Expected Market Capacity *c*				
Rank of entrant	**1**	**2**	**3**	**4**	**5**
1	7.50	7.50	7.50	7.50	7.50
2	–10.00	7.50	7.50	7.50	7.50
3	–10.00	–10.00	7.50	7.50	7.50
4	–10.00	–10.00	–10.00	7.50	7.50
5	–10.00	–10.00	–10.00	–10.00	7.50
6	–10.00	–10.00	–10.00	–10.00	–10.00
7	–10.00	–10.00	–10.00	–10.00	–10.00
Industry equilibrium number of entrants (i)	1.75	3.50	5.25	7.00	7.00

Table 2: Experimental Design

Part 1: General knowledge quiz: 14 binary questions (no feedback provided)

Part 2: Market entry game (Block 1): Subjects randomly assigned to groups of seven players; five rounds of entry decisions with different competitors in each round (no feedback between rounds). Markets vary by size (c) and risk: some have known capacity, others have risky capacity.

Part 3: Partial feedback provided: Group A receives feedback on their own raw scores; Group B on the overall distribution of scores.

Part 4: Market entry game (Block 2): five rounds of entry decisions, as before.

Part 5: Elicitation of beliefs, risk aversion, demographic information

Part 6: Overview of results; payments

Table 3: Mean Number of Entrants by Market Capacity and Type						
(N = 112 subjects; 560 entry decisions)	**Known value of *c***					
Known Markets	**1**	**2**	**3**	**4**	**5**	**Mean**
M = Mean number of Entrants	1.88	2.00	3.75	6.13	6.62	4.08
R(*c*) = Ratio of M to market capacity *c*	1.88	1.00	1.25	1.53	1.32	1.36
R(*i*) = Ratio of M to industry equilibrium *i*	1.07	0.57	0.71	0.88	0.76	0.78
Average profit (loss) per round	-1.26	14.98	14.98	8.75	21.28	11.75
	Possible values of *c*					
Risky Markets	**0-1-2**	**1-2-3**	**1-3-5**	**2-4-6**	**3-5-7**	**Mean**
M = Mean number of Entrants	3.50	1.25	5.87	5.75	4.00	4.07
R(*c*) = Ratio of M to market capacity *c*	3.50	0.63	1.96	1.44	0.80	1.36
R(*i*) = Ratio of M to industry equilibrium *i*	2.00	0.36	1.12	0.82	0.46	0.78
Average profit (loss) per round	-17.50	22.47	-6.23	12.53	47.53	11.76

Table 4: Binomial model (*c* = 2)												
Number of entrants										**Proportion of games**		
0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Sum**	**Mean no. entrants**	**under-entry (<2)**	**correct-entry (2)**	**over-entry (>2)**
.0949	.2656	**.3187**	.2125	.0850	.0204	.0027	.0002	1.0000	2	0.3605	0.3187	0.3208

Note: Proportions in the cells are the proportion of games expected to produce each number of entrants when *c* = 2

	Table 5a: Binomial model (known market capacity)											
	Number of entrants									**Proportion of games**		
↓ Capacity	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Sum**	**Mean no. entrants**	**under-entry (<*c*)**	**correct-entry (*c*)**	**over-entry (>*c*)**
1	.3399	.3966	.1983	.0551	.0092	.0009	.0001	.0000	1.0000	1	.3399	.3966	.2635
2	.0949	.2656	.3187	.2125	.0850	.0204	.0027	.0002	1.0000	2	.3605	.3187	.3208
3	.0199	.1044	.2350	.2938	.2203	.0991	.0248	.0027	1.0000	3	.3593	.2938	.3469
4	.0027	.0248	.0991	.2203	.2938	.2350	.1044	.0199	1.0000	4	.3469	.2938	.3593
5	.0002	.0027	.0204	.0850	.2125	.3187	.2656	.0949	1.0000	5	.3208	.3187	.3605
Sum	**.0915**	**.1588**	**.1743**	**.1733**	**.1641**	**.1348**	**.0795**	**.0235**	**1.0000**	3	**.3455**	**.3243**	**.3302**

Note: Proportions in the cells are the proportion of games expected to produce each number of entrants for each value of *c*

	Table 5b: Binomial model (uncertain market capacity)											
	Number of entrants									**Proportion of games**		
↓ Capacity	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Sum**	**Mean no. entrants**	**under-entry (<*c*)**	**correct-entry (*c*)**	**over-entry (>*c*)**
012	.4783	.2207	.1723	.0892	.0314	.0071	.0009	.0001	1.0000	1	.4783	.2207	.3010
123	.1516	.2555	.2507	.1871	.1048	.0402	.0092	.0009	1.0000	2	.4071	.2507	.3422
135	.1200	.1679	.1512	.1446	.1473	.1396	.0968	.0325	1.0000	3	.4391	.1446	.4163
246	.0325	.0968	.1396	.1473	.1446	.1512	.1679	.1200	1.0000	4	.4163	.1446	.4391
357	.0067	.0357	.0851	.1263	.1443	.1393	.0968	.3658	1.0000	5	.3981	.1393	.4626
Sum	**.1578**	**.1553**	**.1598**	**.1389**	**.1145**	**.0955**	**.0743**	**.1039**	**1.0000**	3	**.4278**	**.1800**	**.3923**

Note: Proportions in the cells are the proportion of games expected to produce each number of entrants for each market

	Table 5c: Binomial model (all markets)												
	Number of entrants										Proportion of games		
↓ Capacity (mean)	0	1	2	3	4	5	6	7	Sum	Mean no. entrants	under-entry (<*c*)	correct-entry (*c*)	over-entry (>*c*)
1	.4091	.3086	.1853	.0721	.0203	.0040	.0005	.0000	1.0000	1	.4091	.3086	.2823
2	.1232	.2606	.2847	.1998	.0949	.0303	.0060	.0005	1.0000	2	.3838	.2847	.3315
3	.0699	.1362	.1931	.2192	.1838	.1194	.0608	.0176	1.0000	3	.3992	.2192	.3816
4	.0176	.0608	.1194	.1838	.2192	.1931	.1362	.0699	1.0000	4	.3816	.2192	.3992
5	.0034	.0192	.0528	.1056	.1784	.2290	.1812	.2304	1.0000	5	.3594	.2290	.4116
Sum	**.1246**	**.1571**	**.1671**	**.1561**	**.1393**	**.1152**	**.0769**	**.0637**	**1.0000**	**3**	**.3866**	**.2521**	**.3612**

Note: Proportions in the cells are the proportion of games expected to produce each number of entrants for each value of *c*

	Table 6a: Results (known market capacity)												
	Number of entrants										Proportion of games		
↓ Capacity	0	1	2	3	4	5	6	7	Sum	Mean no. entrants	under-entry (<*c*)	correct-entry (*c*)	over-entry (>*c*)
1	.1250	.3750	.1250	.2500	.1250	.0000	.0000	.0000	1.0000	1.8750	.1250	.3750	.5000
2	.1250	.1250	.5000	.1250	.1250	.0000	.0000	.0000	1.0000	2.0000	.2500	.5000	.2500
3	.0000	.1250	.0000	.2500	.3750	.1250	.1250	.0000	1.0000	3.7500	.1250	.2500	.6250
4	.0000	.0000	.0000	.0000	.1250	.1250	.2500	.5000	1.0000	6.1250	.0000*	.1250	.8750*
5	.0000	.0000	.0000	.0000	.0000	.1250	.1250	.7500	1.0000	6.6250	.0000*	.1250	.8750*
Sum	**.0500**	**.1250**	**.1250**	**.1250**	**.1500**	**.0750**	**.1000**	**.2500**	**1.0000**	**4.0750**	**.1000****	**.2750**	**.6250*****

Note: Proportions in the cells are the actual proportion of games producing each number of entrants for each value of *c* (40 games)
Statistical tests for differences from binomial proportions: ***p<.001 **p<.01 *p<.05 (n=8 games of each capacity; 40 total)

	Table 6b: Results (uncertain market capacity)												
	Number of entrants										Proportion of games		
↓ Capacity	0	1	2	3	4	5	6	7	Sum	Mean no. entrants	under-entry (<*c*)	correct-entry (*c*)	over-entry (>*c*)
012	.0000	.1250	.1250	.2500	.2500	.1250	.1250	.0000	1.0000	3.5000	.0000*	.1250	.8750**
123	.2500	.2500	.5000	.0000	.0000	.0000	.0000	.0000	1.0000	1.2500	.5000	.5000	.0000
135	.0000	.0000	.0000	.1250	.0000	.2500	.1250	.5000	1.0000	5.8750	.0000*	.1250	.8750*
246	.0000	.0000	.0000	.0000	.2500	.1250	.2500	.3750	1.0000	5.7500	.0000*	.2500	.7500
357	.0000	.0000	.2500	.3750	.0000	.0000	.2500	.1250	1.0000	4.0000	.6250	.0000	.3750
Sum	**.0500**	**.0750**	**.1750**	**.1500**	**.1000**	**.1000**	**.1500**	**.2000**	**1.0000**	**4.0750**	**.2250***	**.2000**	**.5750***

Note: Proportions in the cells are the actual proportion of games producing each number of entrants for each market (40 games)
Statistical tests for differences from binomial proportions: ***p<.001 **p<.01 *p<.05 (n=8 games of each capacity; 40 total)

	Table 6c: Results (all markets)												
	Number of entrants										Proportion of games		
↓ Capacity (mean)	0	1	2	3	4	5	6	7	Sum	Mean no. entrants	under-entry (<*c*)	correct-entry (*c*)	over-entry (>*c*)
1	.0625	.2500	.1250	.2500	.1875	.0625	.0625	.0000	1.0000	2.6875	.0625*	.2500	.6875**
2	.1875	.1875	.5000	.0625	.0625	.0000	.0000	.0000	1.0000	1.6250	.3750	.5000	.1250
3	.0000	.0625	.0000	.1875	.1875	.1875	.1250	.2500	1.0000	4.8125	.0625*	.1875	.7500**
4	.0000	.0000	.0000	.0000	.1875	.1250	.2500	.4375	1.0000	5.9375	.0000**	.1875	.8125**
5	.0000	.0000	.1250	.1875	.0000	.0625	.1875	.4375	1.0000	5.3125	.3125	.0625	.6250
Sum	**.0500**	**.1000**	**.1500**	**.1375**	**.1250**	**.0875**	**.1250**	**.2250**	**1.0000**	**4.0750**	**.1625*****	**.2375**	**.6000*****

Note: Proportions in the cells are the actual proportion of games producing each number of entrants for each value of *c* (80 games)
Statistical tests for differences from binomial proportions: ***p<.001 **p<.01 *p<.05 (n=16 games of each capacity; 80 total)

Table 7: Zero-Order Correlation Matrix										
	(N = 112 subjects; 560 entry decisions)									
	Variable	Mean	SD	1	2	3	4	5	6	7
1	Expected market capacity	3.01	1.42	1.000						
2	Volatility	0.51	0.50	.000	1.000					
3	Rank	7.12	4.10	.000	.000	1.000				
4	Confidence	0.04	0.22	.000	.039	**.241**	1.000			
5	Risk aversion	5.77	2.04	.000	-.037	-.063	.091	1.000		
6	Belief	3.11	1.86	**.659**	-.059	.008	.182	.036	1.000	
7	Gender	0.47	0.50	.000	**-.251**	**-.263**	-.096	**-.211**	-.045	1.000
	Bold: *p* < .001									

Table 8: Random-Effects Logit Model			
MODEL	1	2	3
Expected market capacity	1.877***(0.290)	1.750***(0.302)	2.028***(0.334)
Volatility	2.112***(0.519)	1.833***(0.520)	1.959***(0.538)
Size*volatility	-0.754***(0.165)	-0.701***(0.173)	-0.730***(0.177)
Rank		-0.129***(0.029)	-0.114***(0.030)
Confidence		2.696***(0.568)	2.953***(0.605)
Risk aversion		-0.148**(0.054)	-0.110*(0.056)
Belief			-0.202**(0.090)
Gender			0.644**(0.244)
Constant	-4.943***(0.886)	-2.627**(0.926)	-3.471**(1.026)
$\ln\sigma_{\mu}^{2}$	-0.634 (0.523)	-3.778 (8.247)	-3.407 (6.185)
σ_{μ}	0.728 (0.191)	0.151 (0.623)	0.182 (0.563)
ρ	0.139 (0.063)	0.007 (0.057)	0.010 (0.061)
χ^{2}	76.55	77.43	79.42
N (observations)	560	482	482
N (subjects)	112	97	97
Dependent variable is Entry (0/1)			
Random effects specification is subject ID			
***p<0.001; **p<0.01; *p<0.05			

Figure 1: Excess Entry for Four Market Types

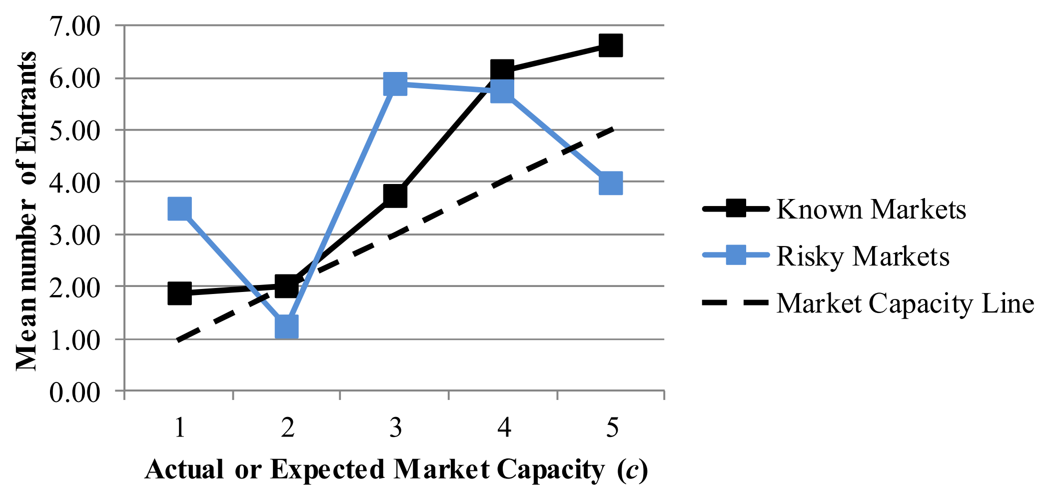
Market Capacity	Risky demand	Known demand
$C = 5$	*Large, volatile market* Excess entry = .80 Mean profits = €47.53 $p < .001$	*Large, stable market* Excess entry = 1.32 Mean profits = €21.28 $p < .001$
$C = 1$	*Entrepreneurial Market* Excess entry = 3.50 Mean profits = – €17.50	*Small, stable market* Excess entry = 1.88 Mean profits = – €1.26 $p < .001$

Market Volatility

Notes:

1. *Excess entry* is the ratio of the mean number of entrants to market capacity *c*
2. *p* values are two-tailed tests of the pairwise difference between the entry ratio of the market shown and the entry ratio in the entrepreneurial market

Figure 2: Number of Entrants for Known and Risky Markets



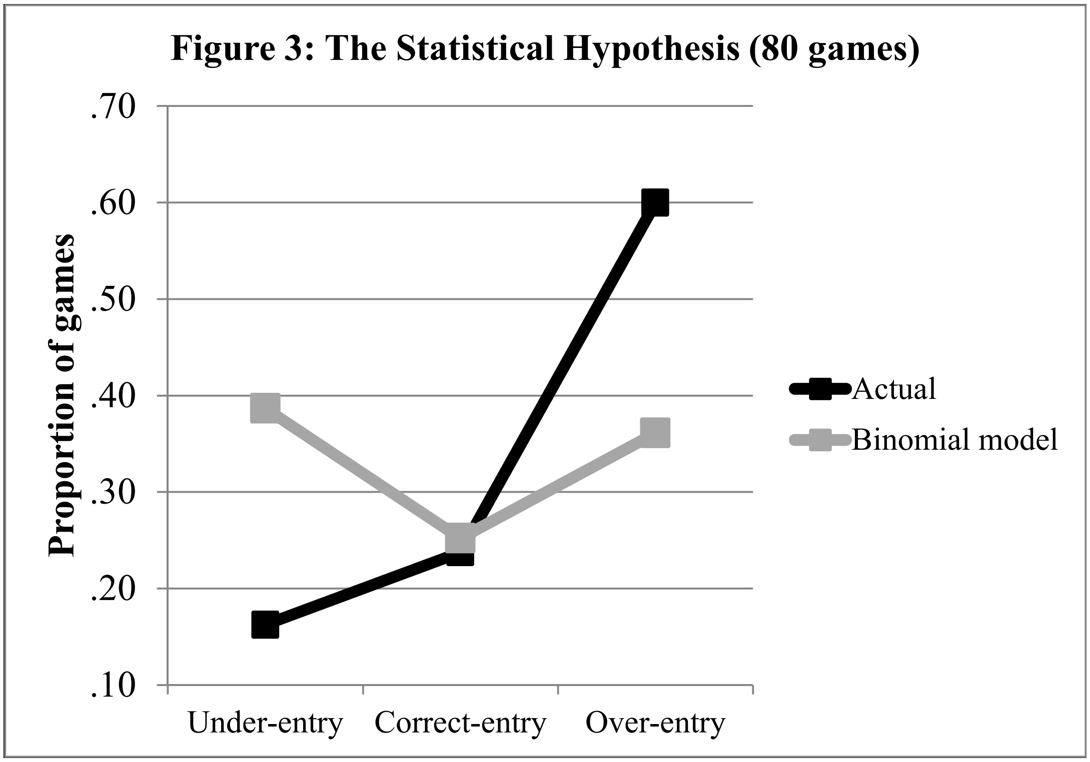


Figure 3: The Statistical Hypothesis (80 games)
Proportion of games
.70
.60
.50
.40
.30
.20
.10
Under-entry
Correct-entry
Over-entry
Actual
Binomial model