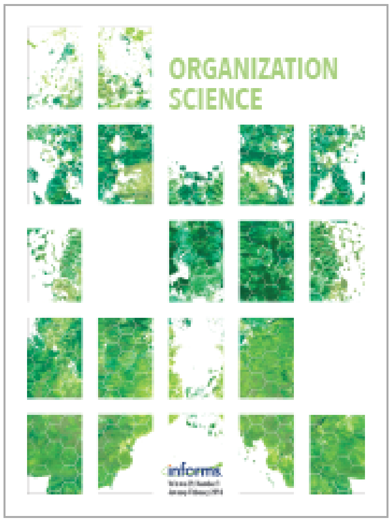

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The Impact of Overconfidence and Ambiguity Attitude on Market Entry

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Abstract. We study the behavioral drivers of market entry. An experiment allows us to disentangle the impact on entry across different types of markets of two key behavioral mechanisms: overconfidence and attitude toward ambiguity. We theorize and show that the causal effect of overconfidence on entry is limited to skill-based markets and does not appear in those that are chance based. Moreover, we also find that, independent of confidence levels, individuals exhibit ambiguity-seeking behavior when the result of the competition depends on their skills, which, in turn, leads to higher levels of entry. This preference for ambiguity thus can explain results that have previously been attributed to overconfidence. Our results challenge existing literature that has inferred overconfidence from differential entry levels across types of markets.

Supplemental Material: The online appendix is available at https://doi.org/10.1287/orsc.2019.1300.

Keywords: behavioral strategy • ambiguity • market entry • overconfidence • entrepreneurship

Introduction

Many of the key strategic actions made by individual decision makers and firms can be characterized as resulting in excess market entry. For example, close to 75% of those who choose careers in entrepreneurship would have been better off as wage workers (Hamilton 2000), and almost 80% of angel investors never recoup their money (Piazza 2017). Similar proportions describe the outcome of corporate decisions because only less than 20% of mergers actually achieve the expected revenue synergies (Christofferson et al. 2004). Likewise, a majority of new products introduced fails within the first year (Christensen 2013), despite overwhelmingly strong managerial beliefs about their potential for success (Simon and Houghton 2003). Finally, excess professional trading in financial markets results in an average loss in net returns exceeding two percentage points every year (Barber and Odean 2001). In short, a vast range of business settings shows signs of excess market entry. However, scholars struggle with causal identification of the behavioral mechanisms that explain these decisions. Our paper seeks to help close this important gap.

We study the behavioral drivers of market entry in strategic contexts with two characteristics that are virtually omnipresent across most markets and shared by all examples in the previous paragraph. First, these settings are inherently ambiguous—that is, the distribution of probability over events (e.g., success or failure) is unknown, and instead, decision makers must rely on essentially subjective priors (Knight 1921, Csaszar 2013, Toh and Kim 2013). Second, the ambiguity in such settings, and the associated payoff, is likely to be perceived by decision makers as related to their own skills, often in comparison with rivals (Wu and Knott 2006). These characteristics imply that at least two distinct behavioral mechanisms could explain entry into the ambiguous, skill-based markets on which we focus in this study: overconfidence and/or positive attitude toward the source of ambiguity.

Overconfidence has often been associated with excess entry because in such settings, decision makers may tend to overestimate their own role and the importance of their own skills in determining future states of the world, at the same time underestimating the random component (Tversky and Fox 1995). Consequently, we could observe surplus entry among decision makers who are overconfident in their skills—that is, who overestimate their abilities relative to those of competitors (Camerer and Lovallo 1999, Dushnitsky 2010). For example, speculating on the reasons for firms' overwhelmingly poor average post-acquisition performance, Warren Buffett famously stated: "managers [are] apparently mesmerized by their childhood reading of the story about the frog-kissing princess. Remembering her success, they pay dearly for the right to kiss corporate toads, expecting wondrous transfigurations. . . . We have observed many kisses but very few miracles" (Miles 2003, p. 13). In line with this metaphor, excess acquisition activity may occur if managers are willing to bid up the price for the target firm in order to exercise their own "kiss" because they wrongly believe it to be exceptionally proficient; that is, they have overly positive beliefs about their own skills. Indeed, Malmendier and Tate (2008) argue that overconfident chief executive officers (CEOs) are 55% more likely to undertake a merger compared with their less confident counterparts.

The ambiguous nature of the market could, however, also result in too many entrants if, independent of their beliefs about chances of success (and their level of overconfidence), decision makers show a preference for ambiguous gambles. This would imply that in such markets, potential entrants are more willing to act based on their beliefs. Using Buffett's analogy, managers may strictly prefer to do the kissing rather than betting on red and spinning the roulette wheel, even if they subjectively judge that they have an equal chance of transforming the toad into a prince as winning on red. In other words, managers may not be overconfident in their skills but still decide to undertake a merger or acquisition because they have a particularly positive attitude toward the source of ambiguity associated with such action.

Yet, despite the theoretical distinctness of overconfidence and attitudes toward ambiguity, extensive prior literature on the underpinnings of entry has failed to disentangle them empirically and, in fact, often confounds them conceptually. Indeed, prior work has routinely inferred the role of overconfidence from differential levels of entry into comparable skill- and chance-based markets or simply from excess entry into skill-based games. For example, in a laboratory setting, Camerer and Lovallo (1999, p. 314, emphasis added) state that "when subjects' post-entry payoffs are based on their own abilities, individuals tend to *over-estimate their chances of relative success* and enter more frequently (*compared to* a condition in which payoffs do not depend on skill)." Similarly, Malmendier and Tate (2005, p. 2663) state that "if a CEO persistently exercises options later than suggested by the benchmark, we infer that he is overconfident. . ."

Although intuitively appealing, such reasoning is conditional on an important implicit assumption that has received little attention in the literature. The overconfidence inference would be true only if entry into comparable skill- and chance-based games was identical for confidence-neutral individuals. We argue (and provide empirical evidence) that this assumption is false and hypothesize a distinct behavioral mechanism that could explain such decision-making patterns. In particular, we posit that a positive attitude toward ambiguity is another element that may play an important role in the decision to enter a given market. This mechanism is independent of confidence and helps explain differential entry when outcomes depend on relative perceived skills compared with a market in which outcomes are determined randomly. Hence, we offer a first empirical test of the joint importance of these two behavioral mechanisms in explaining entry into competitive games.

A third important potential behavioral explanation for excess entry in the types of markets that we study is that of a distinct competence for the skill in question. The competence hypothesis (Heath and Tversky 1991) implies a general and ambiguity-independent preference among individuals for betting on events related to their area of competence (or on events for which they consider themselves knowledgeable) rather than on random events.[1] This mechanism has received consistent empirical support in the literature, especially in situations in which outcomes are independent of the focal individual's skill but individuals have an apparent competence in forecasting outcomes. Research in this area has focused, for example, on individuals placing bets in sports and comparing bets between those who are competent in the sport in question and those who are not (Tversky and Fox 1995, Heath and Tversky 1991). In our study, we differentiate our analysis from tests of the competence hypothesis by focusing on entry decisions that are contingent on relative performance, in which individuals exert effort that directly translates into outcomes, and we also independently control for the effect that competence might have on entry.

Like many before us (e.g., Falk and Heckman 2009), we use a laboratory setting to make more precise claims about causality. A key novelty is to analyze the causal relationship between overconfidence and entry by relying on a novel non-deceptive treatment that allows us to exogenously shock the level of confidence that individuals have about their own skills. Therefore, rather than infer overconfidence from entry choices, we first manipulate its level directly and then observe outcomes. A second novelty is to clearly separate the attitude toward ambiguity from the overconfidence mechanism. To do so, we precisely measure the distribution of the participants' beliefs about their chances of success in a competition that depends on their relative performance on a skill-based test. With this information, we can compare the relative willingness to enter chance- and skill-based games that have been judged by the participant as having an equal probability of success—thus uniquely revealing the effect of the attitude toward ambiguity on entry.

Consequently, our results are novel. We find that decision makers exhibit ambiguity seeking when the result of the competition depends on their skills, independent of their level of confidence and of their competence. This finding stands in contrast to the Ellsberg paradox (Ellsberg 1961) and subsequent evidence of ambiguity aversion in games of chance (for a review of the empirical evidence, see Camerer and Weber 1992) and natural sources of ambiguity (Abdellaoui et al. 2011).[2] We also show that the causal effect of overconfidence on entry is limited to skill-based games and does not appear in games that are chance based—thus showing that inferring overconfidence from differential entry across types of markets is unwarranted. In terms of the relative economic magnitude of the effects we study, we show that overconfidence can account for a differential between 19% and 26% in the willingness to enter between over- and underconfident groups, depending on the estimation method we use. Ambiguity seeking, by contrast, can account for a 36% differential in entry levels. Consequently, we show that ambiguity attitude is both a theoretically and economically important driver of entry.

Definitions

For clarity, we begin by defining the key constructs that we use in the theory development and operationalize in our experimental design, including: overconfidence, attitude toward ambiguity, and skill- and chance-based games (markets).

Overconfidence results from a biased assessment of one's abilities or beliefs. More specifically, overconfidence can be divided into three categories: overestimation, overprecision, and overplacement (Moore and Healy 2008). Both overestimation and overprecision are absolute biases, whereas overplacement is relative to a relevant comparison set. Overestimation refers to a positively biased perception of one's abilities. In this type of overconfidence, no comparison is made to a reference group: the individual assesses only his or her absolute abilities. For example, an athlete overestimating her performance may believe herself capable of doing 30 pull-ups, whereas a reality check reveals that she can do only 10. The second variety of overconfidence, overprecision, refers to "excessive certainty regarding the accuracy of one's beliefs" (Moore and Healy 2008, p. 502). For example, the same, but now overprecise, athlete might state that with 90% certainty, she can do between 25 and 35 pull-ups. Finally, and corresponding to the type of overconfidence on which we focus in this paper, and one that is likely to play the most significant role in competitive contexts (Cain et al. 2015), overplacement is a relative assessment bias. It refers to an erroneous belief in one's performance or abilities *compared with* a reference group. For instance, a perfectly average athlete who estimates that she is in the top 20% of her pull-ups competition group overplaces her performance relative to 30% of others, who are actually more capable athletes.

Risk and *ambiguity* are two constituents of uncertainty. Following the main tradition in the decision under uncertainty literature (Ellsberg 1961, Wakker 2010), we define risk and ambiguity based on the knowledge of the probability distribution over possible states of the world: *risk* describes a situation in which the distribution of probabilities of events is known and *ambiguity* a situation in which the probabilities are unknown.[3] As an illustration, a bet that offers $100 on the flip of a coin if the outcome is tails is considered a risky option; indeed, assuming that the coin is fair, the probability of winning is known—that is, 50%. In contrast, a bet that pays $100 if the price of a specific stock increases is ambiguous; here the decision maker does not know the probability of the winning event.

Attitude toward risk (or *risk attitude*) denotes a positive, negative, or neutral preference for a risky option compared with its expected value. Risk-seeking (averse) individuals assign to the risky prospect a value that is above (below) its expected value and therefore choose the risky (sure) over sure (risky) option.[4] As an illustration, imagine that two people are offered the chance to receive $100 on the flip of a fair coin or the certainty of receiving $50. If the first individual decides to flip the coin and the second does not, we say that the first has a more positive attitude toward risk than the second (in fact, the first is risk seeking whereas the other is risk averse).

Attitude toward ambiguity (or *ambiguity attitude*) denotes a positive, negative, or neutral preference for unknown (compared with known) distributions over events. For instance, imagine that we now give the same two individuals the possibility of winning $100 by betting on whether the price of a specific stock increases tomorrow. For the sake of the example, we assume that both individuals believe that there is a 50% chance that the stock price increases.[5] If the first one (who took the coin-toss bet) decides to take the certain payment of $50 and the second (who previously refused the coin-toss bet) decides to gamble, we can say that the first has a negative attitude toward ambiguity, whereas the second has a positive attitude toward ambiguity. In this case, the outcomes of neither the coin toss nor the bet on the stock price depend on the skills of the focal individuals and hence are not subject to overplacement bias, as defined earlier.

One of the difficulties with theorizing and testing attitudes toward ambiguity is that this attitude is a relative (*compared* with risk attitude) rather than absolute measure. In other words, although an attitude toward risk can be measured on an absolute scale, an attitude toward ambiguity captures the difference "between behavior under unknown probabilities and behavior under known probabilities (risk)" (Wakker 2010, p. 278). Our measurement approach is consistent with this definition.

Chance-based games refer to risky gambles in which the outcomes depend on realizations of the world that are independent from the actions or the skills of the focal individual. Examples of such games include a coin toss, a lottery, and bingo. By contrast, *skill-based games* are settings in which outcomes are based on factors that remain (at least partially) under the control and are believed to be affected by actions of the focal individual or firm. Examples of such games include Texas hold 'em poker, promotional tournaments, product-market competition, relative grade point average performance, or most competitive market settings, such as mergers and acquisitions and innovation races.

Theory and Hypotheses

Excess Entry

Our main contribution is in better explaining, theorizing, and empirically disentangling the behavioral drivers of excess entry in competitive markets, with a particular focus on separating ambiguity attitudes from overconfidence—two key behavioral mechanisms that the prior literature has confounded. Although our focus is on descriptively prevalent patterns of behavior that depart from expected utility theory, the theoretical explanations that account for what seems to be excess participation in a vast range of competitive games and markets encompass conditions under which such choices could be consistent with a rational calculus.[6] However, overwhelming evidence now shows that such decision-making criteria are largely insufficient for fully explaining market dynamics (Åstebro et al. 2014). Thus, such entry decisions need to be better understood in terms of outcomes of systematic mistakes made by boundedly rational decision makers. Accordingly, a growing body of work in this area analyzes various biases and heuristics that affect individuals' and firms' propensity to participate in games and markets. From this perspective, an excessive level of entry can be explained by two main distinct behavioral mechanisms: (1) errors in the estimation of the probability of receiving the payoff and (2) an intrinsic attitude toward the source of uncertainty and its associated payoffs.

The first argument is that excess entry is due to an incorrect assessment of the chances of success on the market, especially when success is perceived to depend on one's own skills. For instance, managers and entrepreneurs can have a (positively) biased perception of their chances of having positive returns (i.e., they are overconfident), which may lead to an excessive level of entry. Related to this argument, excess entry could also occur if potential entrants have a biased perception of the competitive landscape. For instance, managers usually underestimate the number of their competitors and, hence, overestimate their probability of success (Simonsohn 2010). The second behavioral mechanism posits that decision makers considering entry may have a particularly positive disposition toward uncertainty, thus increasing their likelihood of participation. For instance, managers and entrepreneurs may show a positive attitude toward risk and ambiguity, preferring both gambles to sure payoffs as well as putting their career on the line as opposed to gambling in a casino.

However, disentangling these two behavioral mechanisms driving entry has proved to be challenging both theoretically and empirically. To do so, our paper builds most closely on a foundational study by Camerer and Lovallo (1999), who adapted an experimental design originally developed by Kahneman (1988) and later updated by Rapoport et al. (1998). Camerer and Lovallo (1999) studied entry decisions in an experiment with a competitive game in which the participant's payoff depended on his or her rank among all entrants. This rank, and thus the payoff, was determined either randomly (random condition) or based on the subject's performance on a test (skill condition). The authors found greater entry in the skill condition, even though participants correctly forecasted that more of them would be willing to enter in the skill condition than in the random condition. They attributed this finding to participants' overconfidence in their own skills. However, although much of the subsequent literature built on this finding, the study did not contain any treatment or actual measure of overconfidence, nor did it account for an alternative explanation that positive attitude toward ambiguity would favor entry into the skill condition. Thus, it still remains an open question which mechanism actually drives entry choices in these settings. In this paper, we take a step toward closing this important gap.

The Impact of Overconfidence on Entry. The relationship between confidence and entry into competitive and random markets/games has been the subject of analyses across several research streams, and in general, prior work reports a positive correlation between these two constructs. For instance, overconfidence is associated with increased gambling behaviors (Goodie 2005) and excess trading, with the consequence of forgone profits (Grinblatt and Keloharju 2009, Odean 1999). Similarly, overconfident CEOs tend to overestimate the returns from investment projects (Malmendier and Tate 2005) and underestimate the likelihood that new projects will fail (Galasso and Simcoe 2011).

Managers' level of confidence also seems to be related to increased entry into competitive markets, as proxied by the introduction of new products (Simon and Houghton 2003) and the size of the premium paid for acquisitions (Hayward and Hambrick 1997).

This behavioral trait has often been cited as an important factor to explain excess entry into entrepreneurship. Hayward et al. (2006) propose that overconfidence in knowledge, prediction ability, and the personal abilities of founders together can explain why so many new ventures are created, considering the high chances of failure. Compared with managers, entrepreneurs show a higher propensity to be overconfident (Busenitz and Barney 1997) because they believe that their own chances of success are vastly higher than those of comparable entrepreneurs (Cooper et al. 1988, Simon and Shrader 2012, Hvide and Panos 2014). This basic finding across settings, however, may mask other behavioral mechanisms, such as attitude toward risk and ambiguity, and it is predominantly based on correlational studies (Åstebro et al. 2014). Therefore, we are careful to hypothesize and measure these effects independent of attitude toward risk and ambiguity and to establish causation.

Overconfident individuals who suffer from an overplacement bias and who hence overestimate their own ability relative to peers should perceive their chances of success in competitions that depend on their skills as strictly higher than they really are. In particular, the greater this bias, the greater should be individuals' willingness to enter competitive skill-based contests. At the same time, no theoretical link exists between overconfidence and perceived likelihood of success in chance-based games because those games do not depend on skills but, rather, on luck. Therefore, individuals' confidence in their own skills should play no role in the decision to enter a competition in which they have no possibility of linking the likelihood of various outcomes to their own skills. This leads us to the following two hypotheses.

Hypothesis 1. *Overconfidence increases entry into skill-based games.*

Hypothesis 2. *Overconfidence does not affect entry into chance-based games.*

The Impact of Attitude Toward Ambiguity on Entry. Ambiguity attitude is likely to affect entry decisions independent of the mechanism of overconfidence discussed earlier. This is because the very fact that a given decision is characterized by an unknown distribution of probability of success can make it more (or less) attractive to the decision makers compared with a nonambiguous risky prospect. However, whether decision makers show a positive, neutral, or negative attitude toward ambiguity is likely to crucially depend on the nature of the focal entry decision, thus making excess entry more or less probable. If individuals were ambiguity averse, then we should observe a decreased level of market entry compared with comparable chance-based games. Interestingly, if people were ambiguity averse in their choices, then inferring overconfidence from excess entry into skill-based games (as in Camerer and Lovallo 1999) would *under*estimate the impact of this bias on entry choices. In contrast, if focal decision makers exhibited positive attitudes toward ambiguity, then we should observe increased levels of entry, and such inference would *over*estimate the role of overconfidence up to a point of potentially showing a spurious relationship.

Prior literature shows that ambiguity attitudes are crucially dependent on the contextual factors that describe the nature of the focal task and market in question. When the source of ambiguity is external and concerns a context in which one has little agency, a frequent pattern observed in the foundational decision-making literature is that people are generally ambiguity averse—that is, they usually prefer to bet on known probabilities (risk) rather than on unknown probabilities (ambiguity). The classic Ellsberg (1961) paradox documents this pattern of behaviors in the context of choice between bets on known and unknown distributions of colored balls in urns (for a review of the empirical evidence, see Camerer and Weber 1992). Similarly, Abdellaoui et al. (2011) more recently found that a majority of people prefers to bet on a random draw with known probabilities rather than on ambiguous external events such as the temperature in a city or a stock index, even when judging the ambiguous and the risky events as equally likely to happen. Ambiguity aversion has also frequently been observed in other natural settings, such as insurance or medical decisions (for a review, see Machina and Siniscalchi 2014).

However, there is also evidence that in some markets ambiguity attitude is likely to be reversed, turning from ambiguity aversion to ambiguity seeking (for examples of ambiguity-seeking behavior, see Hogarth and Einhorn 1990 and Dimmock et al. 2016). In particular, entrepreneurs and managers make entry choices in contexts in which their decisions are characterized by two contextual features that are likely to lead to ambiguity-seeking patterns: (1) the source of ambiguity is internal and effort dependent, and (2) the resolution of ambiguity (and, consequently, the realization of payoffs) depends on the decision makers' performance relative to rivals.

Related to the first characteristic of ambiguity in a market entry context—that is, internal and effort dependent—Heath and Tversky (1991) reported results consistent with ambiguity-seeking attitudes when subjects were confronted with a trivia question and a game of chance with an objective probability equal to the degree of their confidence in their trivia answer. Similarly, Goodie and Young (2007) found that the acceptance of a fair bet was higher for knowledge-based bets than for random bets. Closer to our empirical setting, where the results depend not only on innate skills or abilities but also on the effort exerted to solve a task, Howell (1971) designed an experiment in which participants were presented with series of pairs of equiprobable bets that had both a chance and an ambiguous component (that depended on the participant performance at throwing darts). The author found that people preferred to bet on a game in which the proportion of the ambiguous component was higher, suggesting a potentially positive attitude toward ambiguity.[7] Overall, these results are consistent with the finding of Wu and Knott (2006) that entrepreneurial entry increases as the determinants of success over which individuals in question have some agency (e.g., cost uncertainty) gain prominence but decreases as the importance of random conditions (e.g., demand uncertainty) grows. Similarly, in the context of technological diversification, Toh and Kim (2013) observe that firms behave more aggressively when technological uncertainty (which arguably can be resolved with effort) increases.

The second characteristic—that is, the competitive nature of the source of ambiguity—is also particularly relevant to our focus on market entry behaviors and is also likely to lead to ambiguity-seeking attitudes. For example, Klein et al. (2010) reported that, on average, individuals preferred to bet on their relative performance on a spelling error detection task than on a chance event. This is echoed by Grieco and Hogarth (2004), who reported that a higher percentage of people prefer an ambiguous bet over a 50% chance in a lottery when ambiguity depends on their relative performance on a test than when it is chance based.

Prior literature has also indicated a distinct but related mechanism leading to behaviors consistent with ambiguity seeking in skill-based markets: competence. This underlies an important role of knowledge about the focal market in studying the behavioral drivers of entry. Indeed, a mechanism that Heath and Tversky (1991) called the "competence hypothesis" implies a general preference among individuals for betting on events related to their area of competence rather than on random events and a preference for betting on areas of higher rather than lower competence. The competence hypothesis, however, is distinct from our mechanism—that is, ambiguity seeking in market entry—as it "applies both to chance and evidential problems" (Heath and Tversky 1991, p. 7). Such competence-driven behavioral preference, for example, may lead to a greater willingness to bet on roulette as opposed to slot machines (both being chance-based games with known probability distributions) for those knowing how roulette wheels are built. It may also indicate a behavioral preference for related rather than unrelated diversification among managers (see March and Shapira 1987). In addition, there are also important differences between the empirical contexts used in prior tests of the competence hypothesis and market entry literatures (and our context). The former has mostly used prediction tasks in which the outcome depends on the realization of an event that is *external* to the focal decision maker, covering a broad range of contexts, including sports events (Tversky and Fox 1995), financial products (Keppe and Weber 1995, Kilka and Weber 2001), political or social events (Heath and Tversky 1991), and weather (Tversky and Fox 1995). In contrast, most of the experimental literature on market entry has used *internal* sources of ambiguity, in which the outcome depends on the effort and associated performance of the decision makers themselves on tasks such as puzzles and trivia questions (Camerer and Lovallo 1999, Bolger et al. 2008, Karelaia and Hogarth 2010, Cain et al. 2015, Artinger and Powell 2016). To illustrate the difference between those settings, in the former case, a participant could bet on someone else's performance (e.g., the success depends on Kobe Bryant scoring more than 70% in free throws), and in the latter, the participant could bet on his or her own performance (e.g., the success depends on the participant scoring more than 70% in free throws).

In summary, this section points to two additional and partially intertwined explanations for excess entry in skill-based competitions: a positive attitude toward ambiguity and competence in the specific skill that affects outcomes of the competition. Ambiguity seeking is likely to occur when outcomes have unknown probabilities, the source of ambiguity is internal and effort dependent, and the resolution of ambiguity depends on the decision makers' performance relative to that of rivals. These, we argue, are characteristics that describe many market entry choices that entrepreneurs and managers make on a regular basis. Absolute or relative competence in a skill or given market may also drive excess entry, but this mechanism is distinct and ambiguity independent.

Building from these prior insights, we hypothesize that independent of both their level of confidence and their level of competence, individuals exhibit a positive attitude toward ambiguity when the source of ambiguity is internal, such as in competitive games of skill, in which the focal actor exercises some action that determines the outcome. In other words, decision makers have a more positive attitude toward uncertainty for the internal type of ambiguity that we focus on in this paper than for one related to luck. This preference for a skill-based game is solely due to the fact that it is ambiguous and depends on outcomes that are a function of the decision maker's relative performance in general. Consequently, we argue the following.

Hypothesis 3. *Entry is higher into skill-based games than chance-based games because of a positive attitude toward ambiguity.*

Experimental Design

Studying the causal role that behavioral mechanisms such as ambiguity attitudes and confidence can play in entry decisions is notoriously difficult. Recognizing these issues, recent work called for more "attention in experimental work to ambiguity-seeking preferences" (Trautmann and van de Kuilen 2015, p. 109). In particular, a limitation of prior work is that it potentially confounds attitude toward ambiguity and confidence in one's own skills because it does not control for the participants' beliefs about their chances of success. This is because ambiguity attitude can only be inferred from comparing entry decisions into different games or markets after carefully accounting for "unintended variations in belief that may be introduced by the manipulation of ambiguity" (Fox and See 2003, p. 299). In other words, one needs to know both the objective and subjective distributions of payoffs in order to disentangle the extent to which entry is driven by confidence or ambiguity attitudes or both. In our experimental design, we accordingly elicit such beliefs.

To do so, we ran an incentivized experiment with 227 participants at the behavioral laboratory of a major university. Two participants stopped the experiment before the end, and the data for four others were incorrectly saved because of electricity cuts at the laboratory. Our final sample is therefore composed of 221 participants, 54% of whom were women and 46% men. In terms of characteristics, participants' ages range from 18 to 30 years (with a mean of 23), and their fields of study include the humanities (34%), the natural sciences (19%), law (12%), economics (6%), and management (6%). The experiment took the form of a computer-based interview and lasted around 75 minutes for each individual. Participants were informed that they would receive compensation of €15 for showing up and could earn additional money based on their performance on a test or on predictions about their performance.[8] All payments were managed by the laboratory.

Skill- and Chance-based Games

We considered two types of games to test our hypotheses: chance- and skill-based games. For chance-based games, the outcomes are independent of the skills or effort exerted by the subject. Specifically, in a chance-based game $CG_i = (X, p_i; 0)$, the participant has a probability p_i of winning €X and a probability $1 - p_i$ of winning €0. For instance, the game $CG_i = (500, 25\%; 0)$ has a probability of 25% of paying €500 and a probability of 75% of paying €0.

Unlike in the case of chance-based games, outcomes of skill-based games are affected by the actions of participants: they were told that they would be ranked among 100 participants based on their performance on a skill-based task and that their rank would determine the payoff. Specifically, the payoff was based on passing a predetermined threshold of relative performance. A skill-based game $SG_i = (X, r_i; 0)$ pays €X to the top r_i participants (out of 100). For instance, $SG_2 =$ (500, 25; 0) is a game in which the participants win €500 if they are ranked in the top 25 out of 100 and €0 otherwise. We varied p_i and r_i and refer to these values as "market capacities" below.[9]

Experimental Tasks

A summary of our experimental protocol is provided in Table 1. A design such as that of Camerer and Lovallo (1999) provides a natural benchmark for studies dealing with behavioral drivers of entry. However, to disentangle the effect of confidence from attitude toward ambiguity, we had to adapt their design in several ways. First, in Camerer and Lovallo's (1999) design, the number of entrants in both skill- and chance-based games was uncertain. In this case, excess entry could occur if participants "fail to appreciate how many competitors there will be" (Camerer and Lovallo 1999, p. 307). To control for this competitive blind spot mechanism, we fixed the number of entrants. In other words, we removed from the decision the participants' beliefs about others' willingness to enter. Second, Camerer and Lovallo (1999) used several monetary payoffs depending on the rank of the contestants. For instance, in one game, the four best-ranked entrants received \$20, \$15, \$10, and \$5, respectively. In such design, the decision to enter depends both on the perceived likelihood of each of the four winning positions and on the valuation of different prizes, which, for example, may introduce effects of beliefs not only about the first moment but also about higher-order moments for the distribution of prizes (see, e.g., Åstebro et al. 2015 for an experimental study of the impact of the third moment). In contrast, we followed recent studies on market entry (e.g., Bolger et al. 2008, Karelaia and Hogarth 2010, Cain et al. 2015, Artinger and Powell 2016) and used a single monetary payoff in case of success. This allowed us to compare the willingness to bet on two games (skill and chance based) that have not only the same subjective probability of success but also the same monetary payoff and therefore to conclude that the difference observed is due to a difference in attitude toward the two types of uncertainty. Third, we measured the actual willingness to bet instead of a binary decision to enter. Such an approach allowed us to obtain a precise estimate of the premium that participants were willing to pay to bet on skill-based games compared with chance-based games.

Part 1: Skill-based Task. The first part of the experiment consisted of a skill-based task that was later used as a source of ambiguity in the elicitation of the participants' ambiguity attitude. Specifically, participants began by answering 50 questions taken from the Raven's progressive matrices test (see Online Appendix A), a nonverbal multiple-choice questionnaire that has been shown to provide a reliable measure of logical reasoning ability (Raven 2000). Math and logic puzzles have been used in several recent studies analyzing market entry and competition (Niederle and Vesterlund 2007, Karelaia and Hogarth 2010, Cain et al. 2015), and among these logic puzzles, the Raven's matrices test seem particularly well adapted to our context because it has also been widely used to obtain measures of overconfidence (e.g., Burks et al. 2013, Herz et al. 2014, Bruhin et al. 2018). The 50 selected questions were the same for all subjects, asked in the same order, and ranged from easy to difficult. For practical purposes, and after pilot testing, we restricted the time available to answer each question to 50 seconds. We ran a second pilot test to examine the distribution of correct answers given this limit. The average performance was 27 correct answers with a minimum and maximum of 11 and 37 out of 50, respectively.

This task was used to treat the participants' degree of confidence in their performance, as well as measure their competence. At the beginning of the experiment, each participant was randomly assigned to one of three treatment groups: overconfident, underconfident, and neutral. Participants were told that they would receive feedback on a sample of the questions that they had answered (see Online Appendix B for more details on the advantages of this method). The feedback covered 10 of the 50 questions on the test. Halfway through the test, the participants received their first feedback on five questions that they had answered. At the end of the test, they received a second round of feedback on five different questions. Participants in the *overconfident* treatment group received feedback displaying a high percentage of their correct answers. More precisely, the first round of feedback was composed of four of their correct answers and one of their wrong answers, whereas the second round was composed of five of their correct answers. By contrast, participants in the *underconfident* treatment group received feedback displaying a low

Table 1. Experimental Design

Part 1: Skill-based task
- 25 Raven's matrices questions
- Estimation of score and rank
- Feedback about performance (except for the neutral treatment group)
- 25 Raven's matrices questions
- Feedback about performance (except for the neutral treatment group)
- Estimation of score and rank

Part 2: Decision tasks (blocks A, B, and C were randomized)

Block A
- Task A1: Elicitation of willingness to bet (WTB) on chance-based games
  Used to assess the WTB on chance-based games with known capacities and known probabilities, allowing to test Hypothesis 2.
- Task A2: Elicitation of WTB on chance-based games*

Block B
- Task B1: Elicitation of willingness to bet (WTB) on skill-based games based on rank
  Used to assess the WTB on skill-based games with known capacities (same capacities as Task A1, allowing to test Hypothesis 1) but unknown subjective probabilities.
- Task B2: Elicitation of beliefs with respect to rank on skill-based task
  Used to assess the distribution of beliefs (i.e., subjective probabilities) of the participants about their rank, necessary to design the skill-based games used in Task B3, with known subjective probabilities.
- Task B3: Elicitation of willingness to bet (WTB) on skill-based games based on beliefs about one's own rank
  Used to assess the WTB on skill-based games with known subjective probabilities (same probabilities as Task A1, allowing to test Hypothesis 3).

Block C
- Task C1: Elicitation of willingness to bet (WTB) on skill-based games based on score
- Task C2: Elicitation of beliefs with respect to score on skill-based task
- Task C3: Elicitation of willingness to bet (WTB) on skill-based games based on beliefs about one's own score

Part 3: Psychometric tests

*The five games of task A2 focused on capturing the shape of the utility function; a series of ANOVA test confirms the absence of any statistically significant difference between the three groups.

percentage of their correct answers: the first round of feedback was composed of one of their correct answers and four of their wrong answers, whereas the second round was composed of five of their wrong answers (see Online Appendix Figure B.1). Participants in the *neutral* condition did not receive any feedback during the test. The neutral treatment group provides a way to verify that the treatment had the desired effect in both directions by ensuring that the control group is between the underconfident and overconfident groups (for an example of the use of a no-feedback group, see Moore and Klein 2008). The neutral group also provides an opportunity to analyze the effect of the natural variation in participants' confidence (without any treatment) on entry.

In order to verify that the treatment had the desired effect, we asked participants to estimate their rank and their number of correct answers at two points during the Raven's matrices test: halfway through the test, just before receiving the first round of feedback (pre-feedback estimate), and after having received the second round of feedback at the end of the test (post-feedback estimate). A comparison of the pre- and post-feedback estimates between the treatment groups allows us to confirm the success of the treatment. More precisely, we did not expect to see any differences between the pre-feedback estimates across treatment groups, but we did expect to see a statistically significant difference in the post-feedback estimates. Our data are consistent with this expectation.

Part 2: Decision Tasks. The second part of the experiment consisted of several decision tasks. The participants were first shown a 10-minute video that explained the type of questions they would have to answer as well as the real incentive system in place.[10] This section was composed of four main decision tasks. The first two tasks were aimed at measuring the willingness to enter into chance- and skill-based games. The third task was designed to elicit the participants' distribution of beliefs (subjective probability of success) about their rank. The last task was aimed at measuring their attitude toward ambiguity.[11] The order of the games (chance or skill based) was randomized among the participants.

In the first task (A1), we elicited the participants' willingness to enter (proxied with willingness to bet) chance-based games with five different probabilities of positive outcomes (henceforth "market capacities"): 12.5%, 25%, 50%, 75%, and 87.5% (see Table 2). For each game, we used a bisection method to elicit the amount of money that made the decision maker indifferent between entering the game and receiving this amount for sure. This indifference value is called the "willingness to bet" (WTB).[12] In other words, for any fixed amount offered higher than the WTB, the participant would prefer to take the amount and not enter the game. However, if the amount offered was lower than the WTB, the participant would be willing to enter (see Figure C.1 in Online Appendix C).

The goal of the second task (B1) was to assess participants' willingness to enter games whose outcome depended on skill (see Figure C.2 in Online Appendix C). We measured the WTBs of skill-based games $SG_i = (X, r_i; 0)$ using the same method as described in

Table 2. Details of Skill- and Chance-based Games

Task A1	Games used to measure the willingness to bet on chance-based games with known probabilities/capacities				
	CG_1	CG_2	CG_3	CG_4	CG_5
CG_i = (500, p_i; 0)	(500, 12.5%; 0)	(500, 25%; 0)	(500, 50%; 0)	(500, 75%; 0)	(500, 87.5%; 0)
Task B1	**Games used to measure the willingness to bet on skill-based games with known capacities**				
SG_i = (500, r_i; 0)	SG_1	SG_2	SG_3	SG_4	SG_5
	(500, 13; 0)	(500, 25; 0)	(500, 50; 0)	(500, 75; 0)	(500, 88; 0)
Task B3	**Games used to measure the willingness to bet on skill-based games with known subjective probabilities**				
$SG_{k,pi}$ = (500, $r_{k,pi}$; 0)	$SG_{k,12.5\%}$	$SG_{k,25\%}$	$SG_{k,50\%}$	$SG_{k,75\%}$	$SG_{k,87.5\%}$
	(500, $r_{k,12.5\%}$; 0)	(500, $r_{k,25\%}$; 0)	(500, $r_{k,50\%}$; 0)	(500, $r_{k,75\%}$; 0)	(500, $r_{k,87.5\%}$; 0)

Notes. CG_i = (X, p_i; 0) corresponds to a chance-based game paying X with a probability p_i and 0 otherwise. SG_i = (X, r_i; 0) corresponds to a skill-based game paying X if a participant is ranked r_i or better and 0 otherwise. $SG_{k,pi}$ = (500, $r_{k,pi}$; 0) is a skill-based game paying X on a rank $r_{k,pi}$ that a participant k believed he or she had a probability p_i of achieving and 0 otherwise. Because task B1 deals with ranks, values must be integers.

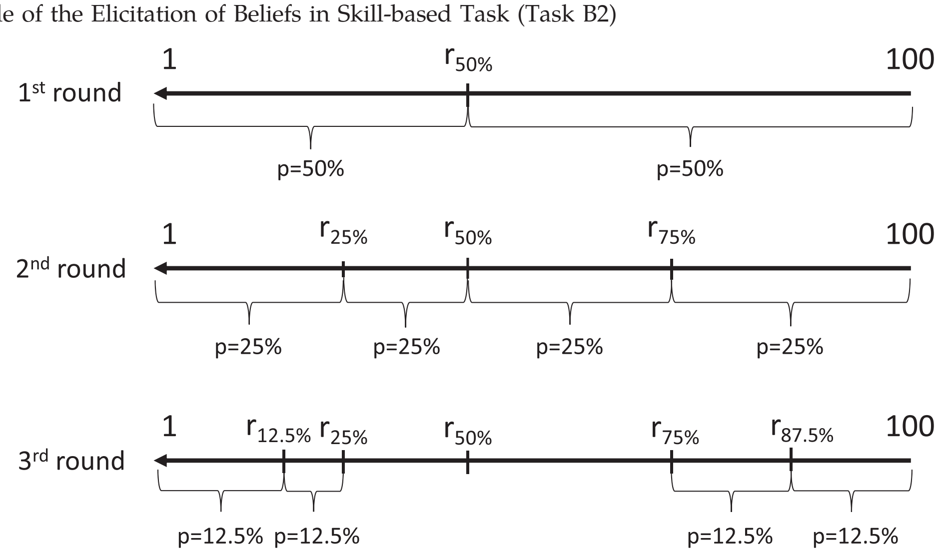
task A1. The games in task B1 were designed in such a way that the capacity of a skill-based game SG_i in task B1 was the same as the capacity of the equivalent chance-based game CG_i in task A1 (see Table 2). Therefore, to understand the differences in willingness to enter chance- and skill-based games, we can directly compare the WTBs of chance-based games CG_i with the WTBs of their equivalent skill-based games SG_i.

As argued earlier, the WTBs in task B1 can mask important alternative behavioral mechanisms. To test our hypotheses, we need to carefully disentangle overconfidence from attitude toward ambiguity, both of which can affect the propensity to enter skill-based games. We also need to account for the impact of competence that could increase entry across games, as discussed earlier. Accordingly, we set out to precisely measure the participants' perceived probability of events, allowing us to match skill-based games with (subjectively) equivalent chance-based games. This task (B2) was a critical phase in our experimental design. More precisely, we needed to find ambiguous events that were judged by the participant as having the same probability as the ones used in the chance-based games of task A1 (12.5%, 25%, 50%, 75%, and 87.5%).[13] To do that, we elicited participants' expectations about their own rank in the skill-based task. Participants can have different beliefs about these ambiguous events despite having the same (i.e., none) information about competitors. For each individual k, we elicited the rank $r_{k,pi}$ for which the participant believed that there was a probability p_i that his or her rank was better than $r_{k,pi}$. For example, in our data, participant 8 believed that he had a probability of 25% of being ranked among the top 41 (i.e., $r_{8,25\%} = 41$), a probability of 50% of being ranked among the top 52 (i.e., $r_{8,50\%} = 52$), and a probability of 75% of being ranked among the top 65 (i.e., $r_{8,75\%} = 65$).

To elicit these beliefs, we used the method developed by Baillon (2008). It is based on the idea that keeping the source of uncertainty constant, individuals are indifferent between betting on two different events when they consider them equally likely. We proceeded in a stepwise fashion. For each participant k, we first found the value $r_{k,50\%}$ for which he or she was indifferent between betting on a game that had a positive payoff if his or her rank was higher than $r_{k,50\%}$ and betting on a game that had the same payoff if that rank was lower than $r_{k,50\%}$. With this process, we obtain, for each participant, two events with an equal probability—that is, 50% (see Figure C.3 in Online Appendix C). For example, participant 8 is indifferent between betting on a game that has a positive payoff if his rank is below 52 (out of 100) or nothing otherwise and a game that has a positive payoff if his rank is above 52 (out of 100) or nothing otherwise. By repeating this process (see the second round in Figure 1) and separating each event with a probability of 50% into two equally likely events, we obtain four events that are perceived by the participants as having a probability of 25%. By repeating this process one last time (see the third round in Figure 1), we can define skill-based games that have the same probability distributions as the chance-based games used in task A1 (see Table 2 and Figure 2 for an illustration of participant 8's answers).

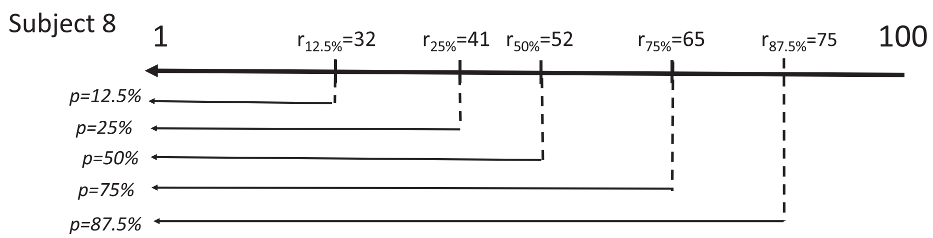
Armed with these beliefs, in the last task (B3), we again measured the WTB on skill-based games. This time, however, we used the actual ranks that corresponded

Figure 1. Example of the Elicitation of Beliefs in Skill-based Task (Task B2)



Notes. This figure provides an example of a possible participant's distribution of beliefs about his or her rank. The distribution in the example is not symmetrical because our elicitation method does not assume any particular function form and allows for both symmetrical and skewed distributions.

Figure 2. Illustration of a Participant's (No. 8) Beliefs About His Own Rank



to the participants' beliefs (elicited in task B2). For example, whereas in task B1 we elicited the WTB on a skill-based game that rewarded the top 25% performers, in task B3 we elicited the WTB on a skill-based game that rewarded the rank that a given participant *believed* he or she had a 25% probability of attaining (based on his or her answers in task B2). For instance, in task B2, participant 8 assigned a probability of 25% of being ranked among the top 41 out of 100. Therefore, we measured his WTB on a game that paid €500 if he was ranked among the top 41 and €0 otherwise (see Figure 2). We could then compare it with his willingness to bet on a chance-based game that paid €500 with a 25% probability and €0 otherwise. We repeated this exercise for each of the five probabilities: 12.5%, 25%, 50%, 75%, and 87.5%.

Part 3: Psychometric Tests. At the end of the experiment, we used a series of psychometric tests to verify that the treatment did not affect constructs that have been shown to be related to overconfidence. We measured individuals' level of optimism using the Life Orientation Test (Scheier et al. 1994). Further, self-esteem was measured with the Rosenberg self-esteem scale (Rosenberg 1989). We also wanted to verify that the treatment affected the participants' confidence only in their task-related skills but not in domains unrelated to the task. To do so, we asked the participants for their height and asked them to rank their height as a percentile of that of the population. We specifically chose the participants' height because it has been shown to be positively associated with cognitive abilities (Case and Paxson 2008), and the estimated relative height could be associated with a general feeling of confidence. Finally, during a pilot study with 54 participants, we verified that the treatment had no effect on their affect, as measured with the Positive and Negative Affect Schedule (Watson et al. 1988).

Implementation of Real Incentives

Before taking the Raven's matrices test, participants were told that they could earn extra money (beyond the €15 participation fee) depending on their performance on the Raven's matrices test and on the accuracy of their estimated performance (more details are in Online Appendix A). In addition, the decision tasks had a real incentive system in place. Before starting the second part of the experiment (i.e., the decision tasks), participants were informed that a random draw would be held at the end of the study and that they would be eligible to have one of their choices selected and played for real. It was made clear to the participants that all the questions they answered during the experiment would be eligible. At the end of the study, we randomly selected two participants. For each participant, we randomly selected one question that he or she had answered. Depending on the question selected and on the answer, the monetary gain could depend on a random draw, on the participant's performance, or be guaranteed. The two participants selected earned an average of €457.

Results

We predicted the following three relationships. First, we argued that overconfidence would positively affect the WTB on skill-based games. Second, we posited that overconfidence would not affect the WTB on chance-based games. Finally, we hypothesized that (for an equal perceived probability of success and independently of the level of confidence) the WTB on skill-based games would be greater than the WTB on chance-based games because of a positive attitude toward ambiguity. Before we turn to discussing the results of our hypothesis testing, we present summary performance statistics and the evidence of the effectiveness of our confidence treatment.

Performance on the Skill-based Task and Treatment Check

In Table 3, we summarize the participants' real and estimated performance on the Raven's matrices test, as well as demographic and control variables for the two treatment and neutral groups. On average, participants answered just over 55% of the test questions correctly, with scores ranging from 8% to 80% of the questions answered correctly. When asked for predictions, they slightly underestimated their absolute performance prior to initial feedback, a regularity that (on average) persists after the feedback. In contrast, the average participant overestimated his or her rank prior to feedback (top 46 compared with

Table 3. Summary of Real and Estimated Performance

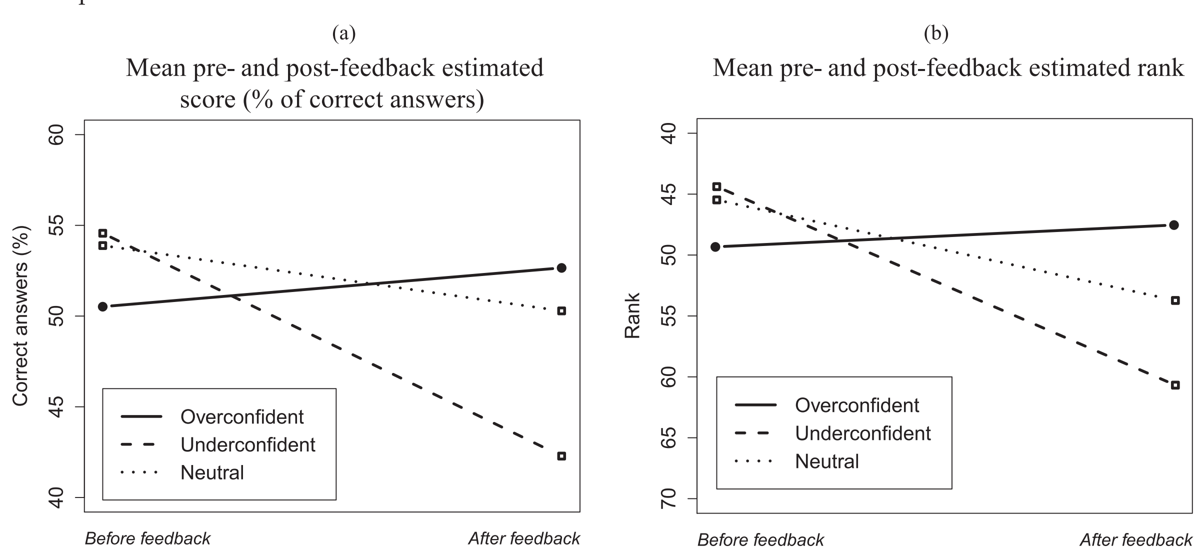
	All	Overconfident	Underconfident	Neutral
Participants	221	73	78	70
Real Score (% of correct answers)	55.38	54.24	55.82	56.06
Pre-feedback estimated score (% of correct answers)	53.01	50.52	54.56	53.88
Post-feedback estimated score (% of correct answers)	48.24	52.66	42.28	50.28
Real Rank (max = 100, best rank = 1)	50.47	53.7	50.03	47.59
Pre-feedback estimated rank	46.36	49.33	44.38	45.47
Post-feedback estimated rank	54.14	47.53	60.68	53.73
Optimism	19.38	19.96	19.24	18.94
Self-esteem	30.87	31.1	30.76	30.77
Estimated height (% of the population)	51.24	48.71	49.09	56.26
Real height (% of the population)	59	56	56	65
Age	22.84	23.15	23.04	22.3
Gender (female)	53.80%	53.40%	53.80%	54.30%
Studies: Law	12.20%	15.10%	9.00%	12.90%
Studies: Humanities	34.40%	39.70%	30.80%	32.90%
Studies: Economics	6.30%	2.70%	7.70%	8.60%
Studies: Management	6.30%	2.70%	6.40%	10.00%
Studies: Sciences	19.00%	20.50%	16.70%	20.00%
Studies: Medical school	4.50%	5.50%	5.10%	2.90%
Studies: Others	17.20%	13.70%	24.40%	12.90%

50 out of 100) but underestimated it following feedback (54 compared with 50 out of 100).

We now turn to the comparisons across treatment groups. Importantly, the level of the actual performance is very similar across three treatment groups. A one-way ANOVA test confirms the absence of statistical difference ($F(2,218) = 0.42$, $p = 0.657$) between the overall test performance across groups, and the same is true ($F(2,218) = 0.68$, $p = 0.508$) when we limit the performance analysis to the post-feedback part of the test. That is, our manipulations did not affect their real performance.

In Figure 3, we illustrate the effect of the treatment on the participants' estimates of their score and rank. A series of one-way ANOVA tests on the estimated scores and ranks confirms that the treatment had the desired effect on the participants' confidence in their performance. The pre-feedback estimated scores of the three treatment groups show no statistically significant difference ($F(2,218) = 1.259$, $p = 0.286$). Similarly, no difference exists in the pre-feedback estimated ranks ($F(2,218) = 0.87$, $p = 0.42$). However, the post-feedback estimated scores ($F(2,218) = 6.213$, $p = 0.002$) and ranks ($F(2,218) = 5.45$, $p = 0.005$) show a

Figure 3. Impact of the Treatment on Estimated Performance



strong difference, indicating concordance with intended treatment effects. A series of paired t-tests shows that participants in the neutral treatment group estimated their rank 8 places out of 100 lower ($p < 0.001$) at the end of the questionnaire than they did halfway through it. This is the case even though the participants' performance showed no difference between the first and second halves of the questionnaire. Participants in the underconfident group estimated their rank 16 places out of 100 lower ($p < 0.001$) at the end of the questionnaire than they did halfway through it. By contrast, participants in the overconfident group estimated their rank 2 places out of 100 higher at the end of the questionnaire than they did halfway through it ($p = 0.124$). Overall, these results indicate that the treatment had the desired effect on participants' confidence. In Online Appendix D, we also check and find that the treatment had the desired effect not only on stated performance estimates but also on the entire distribution of beliefs. Importantly, and as further discussed in the online appendix, these analyses confirm that our treatment affected only the first moment (i.e., mean) but not the second moment (i.e., spread) of the beliefs.

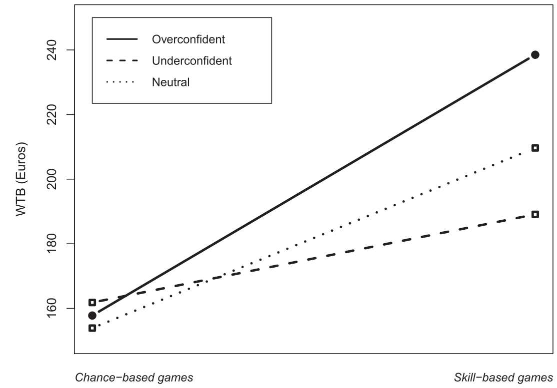
We then verified that the treatment did not affect other constructs that could influence entry choices, thus leading to potentially spurious results. A one-way ANOVA test confirms the absence of any statistically significant difference between the post-treatment levels of optimism ($F(2,218) = 0.991$, $p = 0.373$) and levels of self-esteem ($F(2,218) = 0.088$, $p = 0.915$) among the three treatment groups. We also confirm, using a one-way ANOVA test, the lack of any difference among the three groups ($F(2,218) = 0.256$, $p = 0.774$) in terms of personality-driven overconfidence (confidence about relative height). Furthermore, a series of chi-square tests shows no statistical difference in the proportion of fields of study ($\chi^2(14, n = 221) = 15.594$, $p = 0.34$) or gender ($\chi^2(2, n = 221) = 0.01$, $p = 0.995$) among the three groups. Similarly, an ANOVA test confirms that the three treatment groups did not differ statistically in terms of participants' age ($F(2,218) = 1.764$, $p = 0.174$).

Overconfidence and Entry

In Figure 4, we plot data pertaining to the impact of overconfidence on the average WTB on skill- and chance-based games with equal capacities (i.e., tasks A1 and B1). Consistent with Hypothesis 1, the average WTB of the participants in the overconfident treatment group is greater than that in the underconfident group for the skill-based games (€238.5 versus €189.1, $p = 0.001$). In line with Hypothesis 2, however, we see no differences in the WTB on chance-based games (€157.8 versus €161.6, $p = 0.703$).

These average effects are consistent with Hypotheses 1 and 2. To further verify the robustness of these

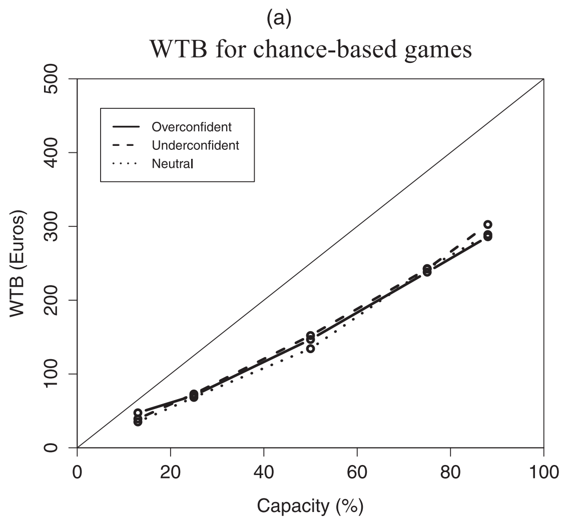
Figure 4. Mean Willingness to Bet (WTB) on Chance-based Games of Task A1 and Skill-based Games of Task B1

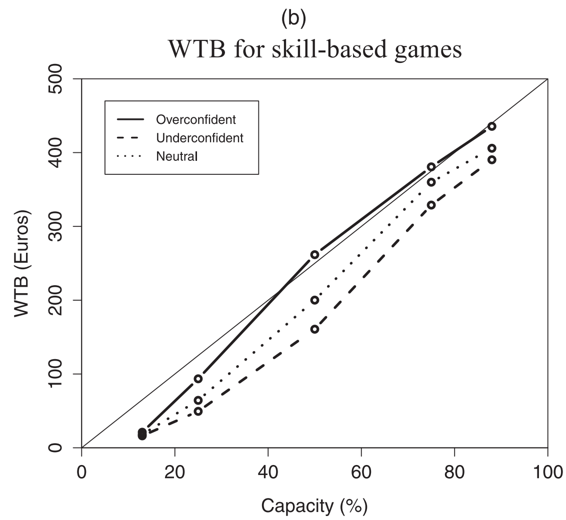


results, we test the impact of our experimental treatment on the WTB on chance-based games (Figure 5(a)) and on skill-based games (Figure 5(b)) separately for each of the five different levels of market capacity. As the left-hand panel of Figure 5 illustrates, the WTBs of chance-based games are similar across the two main treatment groups as well as the neutral condition, irrespective of market capacity. A repeated-measures ANOVA test shows no statistical difference between the two treatment groups ($F(1,751) = 0.224$, $p = 0.636$). For skill-based games, we find a substantially different pattern in the overconfident and underconfident treatment groups. We observe that with the exception of markets with low capacity, the average WTB is consistently higher for the overconfident group than for the underconfident group (see Figure 5(b)). A repeated-measures ANOVA test confirms that a statistically significant difference exists between the two treatment groups ($F(1,751) = 16.14$, $p < 0.001$). More precisely, a series of one-tailed t-tests (see Table 4) shows that the WTB on skill-based games is significantly higher ($p < 0.027$) for participants in the overconfident group than for participants in the underconfident group at all levels of market capacity except the lowest (i.e., the most competitive games).

Finally, and consistent with prior evidence (e.g., Camerer and Lovallo 1999), we observe a greater average propensity to enter into skill-based games compared with chance-based games in the neutral group (€209.7 versus €153.9, $p < 0.001$).[14] Interestingly, the higher WTB on skill-based games occurs even though participants in the neutral group are, on average, slightly underconfident. Indeed, in this group, participants underestimate both their absolute score and expected rank, compared with realized outcomes. Therefore, while these results provide strong support for Hypotheses 1 and 2, they tell us little about the actual comparative propensity to enter across types of games. This is because, in addition to a difference in the beliefs about the probability of success (objective versus subjective),

Figure 5. Mean Willingness to Bet (WTB) on Chance-based Games of Task A1 and Skill-based Games of Task B1 with Same Capacities





participants' attitude (i.e., the way in which they act based on their beliefs) can also differ between the two types of games. We turn to the analysis of these comparative patterns in the next section.

Attitude Toward Ambiguity and Entry

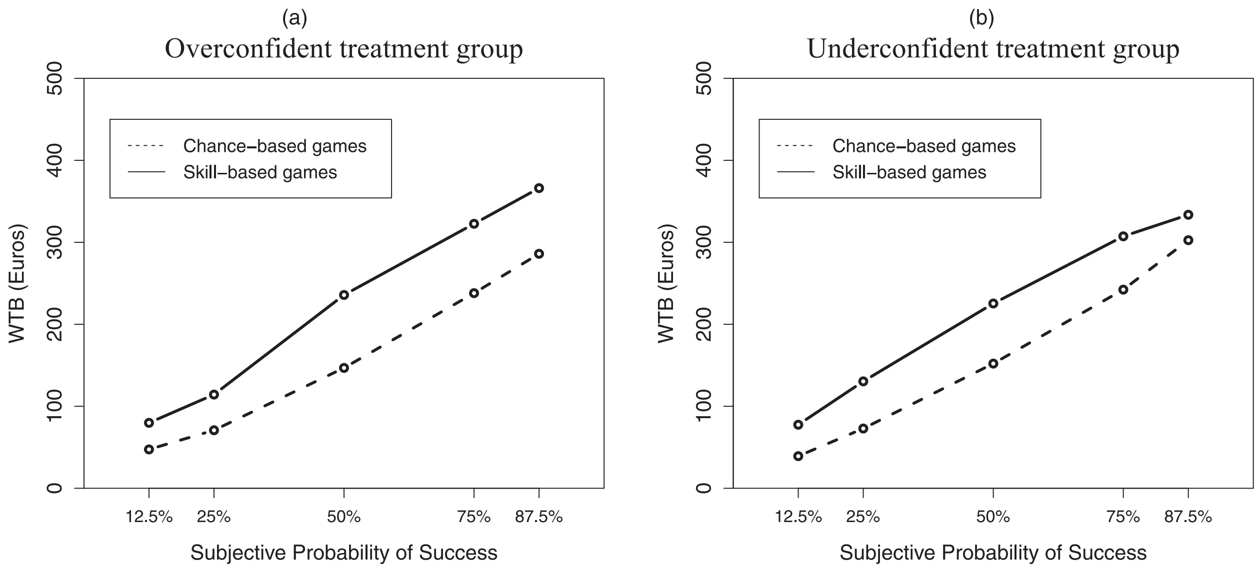
A test of Hypothesis 3 requires that we isolate the entry consequences of attitude toward ambiguity from that of confidence. To do so, we now compare the WTBs on the skill-based games in task B3 (for which we know the subjective probability assigned by the participants) with the WTBs on the chance-based games in task A1 across all three treatment groups. More precisely, we can match games from tasks A1 and B3 so that, for each participant, we compare the willingness to enter a skill-based game whose subjective probability of success is equal to the objective probability of success in a chance-based game in task A1. For example, we compare the WTB on a chance-based game with an objective probability of success of 50% with the WTB on a skill-based game with a subjective probability of success of 50%. Any difference in WTB on such *equivalent* chance-based games of task A1 and skill-based games of task B3 cannot be due to a different perception of the likelihood of success (and therefore to confidence) but only to a difference in attitude toward the source of uncertainty. A full summary of the WTBs obtained in task B3 is in Table E.3 of Online Appendix E.

Figure 6 displays, for the overconfident and underconfident treatment groups, the mean WTBs on the chance- and skill-based games for five levels of probability (12.5%, 25%, 50%, 75%, and 87.5%). We observe that for both the overconfident (left-hand panel) and underconfident (right-hand panel) groups, the mean WTB is higher for skill-based games than for chance-based games at all levels of probability. A repeated-measures ANOVA test[15] confirms that the WTBs of the skill-based games are significantly higher than the WTBs of chance-based games for both the overconfident group ($F(1,72) = 33.07$, $p < 0.001$) and the underconfident group ($F(1,77) = 22.44$, $p < 0.001$). The results are also economically significant. On average, participants are willing to bet 36% more on skill-based games than on equivalent chance-based games. These results are consistent with Hypothesis 3: independently of their level of confidence, people are more willing to bet on a skill-based game than on a chance-based game when they judge that the two games have the same probability of success. Moreover, and importantly, we see no difference in this premium across our treatment groups ($F(1, 747) = 1.595$, $p = 0.21$), indicating that attitude toward ambiguity and confidence

Table 4. *t*-Tests on Willingness to Bet (WTB) on Skill-based Games Based on Rank (Task B1) Between Overconfident and Underconfident Treatment Groups

Game (task B1)	Mean WTB overconfident	Mean WTB underconfident	*p*-Value
(500, 13; 0)	21.05	16.23	0.165
(500, 25; 0)	93.47	49.44	0.014
(500, 50; 0)	261.66	160.67	<0.001
(500, 75; 0)	380.71	328.86	0.027
(500, 88; 0)	435.56	390.27	0.019

Figure 6. Mean Willingness to Bet (WTB) on Chance-based Games of Task A1 and Skill-based Games of Task B3 with Same (Subjective) Probabilities of Success



are indeed distinct behavioral mechanisms driving entry choices.

Our results offer strong support for the hypothesized relationship and show that overconfidence and a positive attitude toward ambiguity are distinct behavioral mechanisms promoting entry into skill-based games. A natural question pertains, however, to the relative magnitude of these two effects. Within the constraints of our data and the confines of our treatment design, we can approximate the economic significance of the relationships that we estimate. We use two alternative methods to quantify the weight of confidence. In the first method, we compute the size of the effect of our exogenous treatment (i.e., overconfident versus underconfident treatment groups) on the WTB on the games of task B1. In the second method, we focus on the neutral group and use the participants' intrinsic level of confidence; we categorize participants who estimated their rank as better (worse) than their achieved rank as intrinsically overconfident (underconfident). For the treatment method, we find that the WTB on the skill-based games is 26% higher for the overconfident treatment group than for the underconfident treatment group. Looking at intrinsic levels of confidence, we report comparable size of the effect: those who are intrinsically overconfident are willing to bet 19% more than those who are intrinsically underconfident. For attitudes toward ambiguity, we estimate the magnitude of the effect by comparing, across treatment groups, the WTB on skill-based games and on equivalent chance-based games. On average, in our sample, the size of the effect of the positive attitude toward ambiguity is greater than the one we saw for overconfidence: an average of 36%.

Robustness Tests

Given the importance of these findings, it is relevant to consider and, to the extent possible, rule out alternative explanations. One important alternative explanation of our findings is that simply receiving feedback (either positive or negative) makes the participants more ambiguity seeking. To rule out this possibility, we run the same analysis with the participants in the neutral group, who did not receive any feedback (see Figure E.1 in Online Appendix E). Here again, a repeated-measures ANOVA test shows that the mean WTB is significantly higher ($F(1, 69) = 19.68, p < 0.001$) for skill-based games than for chance-based games, rejecting the idea that ambiguity seeking is driven by receiving any type of feedback.

We have shown that participants in both the overconfident and underconfident treatment groups, as well as the neutral group, exhibit a higher WTB on a skill-based game than on a chance-based game. Although an increase/decrease in confidence does not affect the ambiguity attitude, one could speculate that this positive attitude toward ambiguity could be driven by individuals who are intrinsically more confident in their skills. We would therefore like to verify that the ambiguity-seeking behavioral mechanism is present independently of the participants' intrinsic level of overconfidence. Moreover, we would also like to show that it is independent of participants' level of competence or feeling of competence, as suggested by the competence hypothesis (Heath and Tversky 1991, Tversky and Fox 1995).

To examine these alternative explanations, we again analyze the neutral treatment group alone, but this time we separate it into two subsamples based on the participants' intrinsic level of confidence (trait 1), level of competence (trait 2), or feeling of competence (trait 3). Participants are classified as having high (low) competence if their score on the skill-based task is higher (lower) than the median score. Similarly, participants are classified as having a high (low) feeling of competence if their estimated score on the test is higher (lower) than the median estimated score.[16] Finally, we use the classification described earlier for the intrinsic level of confidence. In the second column of Table 5, we report the results of a series of repeated-measures ANOVA tests performed with the three different types of traits. These analyses confirm that the participants in our sample who do not receive any confidence treatment bet more on skill-based games than on comparable chance-based games independent of their intrinsic degree of confidence, degree of competence, or feeling of competence. In addition, for each of the three classifications, we ran an ANOVA test on the premium paid by the participants to enter a skill-based game over a comparable chance-based game. This analysis shows that this premium is statistically indistinguishable across the three trait levels (see the third column of Table 5).

These additional analyses further reinforce our confidence that data are consistent with Hypothesis 3 and that the behavioral mechanism we identify is that of a positive attitude toward ambiguity: independent of their level of confidence (and of their level and feeling of competence), people are more willing to bet on a skill-based game than on a chance-based game when they judge the two games as having the same probability of success.

A final concern could be that if the randomization failed, our ANOVA and paired *t*-tests might be subject to bias through the influence of omitted and correlated variables. We have previously tested and found that the randomization appeared to work well. However, to confirm our results even further, we also present results of multivariate analyses where we predict participants' willingness to bet while directly controlling for an array of personal traits (such as gender, age, and field of studies) and behavioral variables (such as optimism, self-esteem, and personality-driven overconfidence). The results of these analyses are consistent with the above-mentioned patterns (see Tables E.4 and E.5 in Online Appendix E).

Discussion

In this paper, we study how overconfidence and attitude toward ambiguity affect entry in strategic contexts that are characterized by uncertain payoffs and skill-based competition. To pin down the causal effects and empirically separate the role of these two behavioral mechanisms, we use a laboratory experiment. In our design, we rely on a novel non-deceptive method to exogenously shock participants' level of confidence in their skills to show a positive causal effect of overconfidence on entry in competitive games based on skill. In contrast, and in line with our prediction, we do not find any effect of confidence on entry in games in which the outcomes are drawn randomly (chance-based games). We further disentangle overconfidence and the attitude toward ambiguity by carefully eliciting participants' subjective beliefs about their performance. Armed with these beliefs, we test our third hypothesis and show that increased entry also occurs because individuals exhibit an ambiguity-seeking attitude when the result of the competition depends on their skills, independent of their level of confidence and of competence.

With these three main results, we offer several contributions to the existing literature on the determinants of market entry, entrepreneurship, and behavioral strategy more generally. First, we show that overconfidence is neither necessary nor sufficient to produce excess entry, independent of the type of the market studied. Our results indicate that inferring that a decision maker is overconfident from observing higher levels of entry or excess investments in, for example, stock options or research and development compared with entry in games of chance is not possible. We thus challenge the implicit assumption underlying much of the literature that has used this inference to link excess entry to overconfidence. In particular, we show that overconfidence only drives entry in skill-based games. Although many competitions are driven by skill, the opportunity to perceive skill as driving returns and thus the entry decision varies across situations and settings, and the role of overconfidence in biasing entry should vary accordingly.

Table 5. Tests for Alternative Explanations

	ANOVA test (type of game) on willingness to bet	ANOVA test (trait group) on premium
High competence	$F(1,32) = 6.386$, $p = 0.017$	$F(1,68) = 0.286$, $p = 0.594$
Low competence	$F(1,36) = 13.93$, $p < 0.001$	
Intrinsically overconfident	$F(1,24) = 8.54$, $p = 0.007$	$F(1,68) = 0.07$, $p = 0.792$
Intrinsically underconfident	$F(1,44) = 11.07$, $p = 0.002$	
High feeling of competence	$F(1,29) = 6.269$, $p = 0.0182$	$F(1,68) = 0.098$, $p = 0.755$
Low feeling of competence	$F(1,39) = 13.72$, $p < 0.001$	

Another major contribution of our paper is in highlighting the critical role that attitude toward ambiguity plays in entry and showing that prior literature has often confounded the role of this behavioral mechanism with that of overconfidence. Although scholars have stressed the importance of uncertainty in strategic decision making (for a recent review and systematization, see Packard et al. 2017), empirical studies on this topic remain in short supply. This is mostly due to the difficulty of measuring beliefs (i.e., subjective perceptions of the probability distribution over the outcomes of interest)—a necessary step in assessing decision makers' attitude toward ambiguity. For example, most of the literature studying drivers of entry into entrepreneurship so far has focused on attitudes toward risk rather than ambiguity (Caliendo et al. 2009, Stewart and Roth 2001). In particular, the focus has been on the idea that entry, often resulting in a monetary loss, could be explained by a lower degree of risk aversion (see the entrepreneurial model proposed by Kihlstrom and Laffont 1979). Yet the consistently documented difference in average risk aversion between entrepreneurs and non-entrepreneurs is too small to explain the large economic penalty that most people suffer from choosing entrepreneurship (Åstebro et al. 2014). One obvious reason for the failure of (lower) risk aversion to fully explain much of the entry into entrepreneurship is that the probability of success for this entry decision is unknown. Our study indicates that excess entry into entrepreneurship can be better explained by a preference for ambiguity. We found that the size of the effect of the positive attitude toward ambiguity was, on average, 36% above the willingness to bet on chance-based games. This is comparable to the typical long-run economic penalty from choosing entrepreneurship. For example, prior work documents the discounted net present value (NPV) of earnings at 35% lower for the median entrepreneur working for 10 years compared with similar wage earners (Hamilton 2000). Our estimates can also help better explain the persistent economic penalty for corporate acquisitions, which seems to hover around –1.5% five-day cumulative abnormal return for public targets, a penalty that further increases significantly when managers are entrenched and thus have more decision-making autonomy—and are potentially more likely to act on biased estimates (Masulis, Wang, and Xie 2007). Interestingly, we find that, given our treatment, the effect of ambiguity seeking on entry is greater than the effect of overconfidence.

Our paper also provides important implications for managers and those designing organizational architectures. First, our results imply that in business situations in which it can easily be concluded that the decision maker's skill matters little (or is less relevant because chance is likely to play a major role), the scope for biased decisions as a result of overconfidence or ambiguity attitudes is likely to be limited. Managers and organizational architects thus should focus more of their attention on monitoring employees and implementing design elements that could help prevent value-destroying entry choices in situations where biased decisions are more likely to occur. For example, under an assumption that skills are not easily portable across industries, our results imply that although entry choice in the form of related diversification is, on average, more likely to be successful than unrelated diversification, it is also likely to be more affected by overconfidence.

A crucial question therefore concerns what organizations can do to take advantage of the growing theoretical understanding of the role that cognitive biases play in entry choices. Although decision-making biases may be very difficult to change and counter at an individual level (for an illustration, see Guilbault et al. 2004), managers and organizational architects often have control over tools that help reduce biased decision making in organizations, thus enhancing firm performance (Lovallo and Sibony 2010, Kahneman et al. 2011). Indeed, rather than debiasing individuals, "firm-level solutions may offer the best way forward" (Powell et al. 2011, p. 1379). However, different biases call for different debiasing strategies, and "understanding [the] causes [of a bias] facilitates identifying when different de-biasing strategies will be effective" (Larrick 2004, p. 319). In highlighting a distinct role that overconfidence and attitude toward ambiguity play in entry choices, our paper points to the importance of recognizing which mechanism is likely to affect entry choices in which context and tailoring organizational remedies accordingly.

If the main goal is to alleviate the bias of overconfidence, then design choices that would effectively mitigate excess entry should aim to increase the alignment of subjective beliefs with those of the true probability of success. For instance, organizing the decision-making process so as to take an "inside view" on a given decision can lead to increased levels of managerial and entrepreneurial overconfidence (Kahneman and Lovallo 1993, Camerer and Lovallo 1999, Bernardo and Welch 2001, Koellinger et al. 2007). Accordingly, designing decision-making processes in a way that encourages taking an "outside view" and using "generalizable aspects of a broad set of problems to make predictions" could be a solution (Kahneman et al. 2011, p. 58). In a similar vein, providing feedback about estimates in an organizational context has been shown to improve calibration—that is, the precision of the beliefs (Russo and Schoemaker 1992). Integrating these two mechanisms (feedback and outside view) structurally, organizations seeking to decrease overconfidence bias may, for instance, put in place tools that provide managers with a more accurate assessment of their own skills and ensure the involvement of heterogeneous opinions, thus potentially decreasing the chance of excess entry. Similarly, the previous literature has found that counterfactual reasoning—that is, thinking of reasons that contradict one's beliefs—tends to reduce the confidence bias about knowledge questions (Koriat et al. 1980), forecasting one's future situation (Hoch 1985), and strategic marketing planning (Mahajan 1992). Interestingly, engaging in counterfactual thinking has also been shown to improve group decision making (Kray and Galinsky 2003). Finally, overconfidence may result in predictable behaviors that organizational design can counter. One organizational design lever that holds a promising prospect is delegation of decision rights. For example, positively biased assessment of one's abilities can lead senior managers to engage in excessive levels of selective intervention (Foss 2003). By delegating decisions to lower management level and credibly committing not to selectively intervene or providing a structure limiting the potential for doing so, managers and organization designers could counter the negative entry consequences of this bias.

Organizational remedies that could help counter nonneutral attitudes toward ambiguity are much less understood, given that the theoretical and empirical literature on this topic is still relatively limited. In general, any solution that counters this bias would not correct the decision maker's mean beliefs about the likelihood of success but rather affect the range of these beliefs—thus reducing (or increasing) the ambiguity surrounding the decision. For example, an organization-level policy that requires decision makers to justify their choices using a narrow range of potential outcomes (as opposed to a wide range) is likely to reduce ambiguity aversion, which is usually observed for external sources of ambiguity (for an illustration of the effect of interval range on ambiguity attitude, see Bowen et al. 1994). While we are not aware of any empirical tests, we expect the opposite to happen for internal sources of ambiguity—that is, using estimates with narrow intervals would reduce ambiguity seeking. Of course, a mean-preserving narrowing/widening of the range will have no impact on the potentially value-destroying role of overconfidence in entry, thus acting solely on ambiguity preference. Similarly, some evidence indicates that the way in which information is presented—for instance, in terms of either conflicting probabilities or probability intervals—could affect decision makers' attitudes toward ambiguity (Cabantous 2007). As an illustration, a manager evaluating an investment opportunity might exhibit a less positive attitude toward ambiguity if presented with two scenarios that forecast either a 40% or 60% chance of success than if presented with one scenario that forecasts a chance of success ranging from 40% to 60%.

Another potential organizational design solution may be inferred from prior work on group versus individual decision rules. For example, Csaszar (2012) shows that increasing the level of consensus needed to make a decision leads to more errors of omission (such as a decision not to enter a potentially profitable market) but decreases the number of commission errors (such as excess entry). Similarly, Keck et al. (2014) found that groups made more ambiguity-neutral decisions than individuals—a finding that is consistent with prior evidence that communication leads to more ambiguity-neutral choices (Charness et al. 2013). Future work could fruitfully test whether consensus level and decision-making aggregation affect ambiguity attitudes in entry choices. Finally, future work should also empirically link and extend the role of key architectural choices that have been shown to affect risk-taking attitudes to ambiguity attitudes. In particular, the design of the three core incentive-system pillars (Milgrom and Roberts 1994)—allocation of property rights, delegation of autonomy, and design of pay systems—is crucial in affecting risk-taking patterns in organizations, a regularity that may extend to ambiguity attitudes as well (Greve 2003, Obloj and Sengul 2012). Similarly, third-party externalities associated with a given strategic decision also shape risk-taking behavior (Bolton et al. 2015), giving rise to important contextual contingencies surrounding entry decision. Practically, debiasing decision increasingly takes the form of using mixed judgment and algorithmic balanced scorecard assessments where the ultimate decision is based on both demonstrated skill and the wisdom of the internal crowd, rather than on the influence of seniority (Mellers et al. 2014).

Of course, our study is not without limitations. First, our data come from the laboratory. Laboratory experiments allow careful control of the decision environment and randomization of the treatment and are thus particularly adapted to the analysis of causal relationships (Falk and Heckman 2009) and of the interaction among several variables (Angrist et al. 2006, p. 186). However, more research using data from the field is needed to replicate our results so as to establish the external validity of our findings. In particular, some elements that appear in natural market competition have been purposefully neutralized in our experimental design to allow for inference. For instance, we fix the number of entrants and vary only the market capacity. In doing so, we mute the "competitive blind spots" (i.e., incorrect estimation of the potential number of competitors) phenomenon. The presence of competitive blind spots nevertheless can also explain excess entry into competitive markets and is worthy of examination as well.

Second, although our experimental protocol allowed negative NPV decisions (e.g., forgoing a sure gain of €400 in favor of a game that yielded €500 with a probability of 50% and €0 otherwise), participants were not exposed to losses. In other words, they were not endowed with resources that they could lose through their entry choices. In real business situations, when such losses loom for the decision makers, other behavioral mechanisms (e.g., loss aversion) may play an additional role in predicting entry. Future research could fruitfully explore this mechanism.

Finally, our paper focuses solely on one of the three core dimensions of overconfidence: overplacement. Although, arguably, this bias is most relevant in competitive contexts, overprecision, the "excessive certainty regarding the accuracy of one's beliefs" (Moore and Healy 2008, p. 502) has also been related to entry into entrepreneurship (Herz et al. 2014) and to excessive market trading (Odean 1999). Again, extending our results to other forms of overconfidence would help build a cohesive behavioral theory of entry.

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Endnotes

[1] For instance, an individual working in a coin factory may prefer to bet on a toss of a coin than on an even number in a roll of the dice.

[2] Sources, or domains, of uncertainty (either risk or ambiguity) can be defined as "groups of events that are generated by the same mechanism of uncertainty, which implies that they have similar characteristics" (Abdellaoui et al. 2011, p. 696). The temperature tomorrow in a given city, the winner of the next Super Bowl, or the winning numbers in the national lottery are events based on different sources of uncertainty. The first two examples are ambiguous, whereas the third one is risky.

[3] Note that sometimes ambiguity is referred to as uncertainty (Knight 1921). Ambiguity would also be present if the probability distribution of an event were to be drawn from one of many known probability distributions, but the decision maker did not know from which one (see Posen et al. 2018).

[4] We adopt a model-free approach of aversion to risk. In some models, such as expected utility, the attitude toward risk is entirely captured by the utility function (for an illustration, see Kihlstrom and Laffont 1979). However, other models, such as prospect theory, consider that risk attitudes depend not only on the shape of the utility function but also on other factors, such as the weighting of probabilities (for an extensive description, see Wakker 2010).

[5] This assumption allows us to isolate, in the example, the attitude toward ambiguity from a difference in beliefs about the likelihood of success. Note that the fact that individuals assign a 50% probability to the winning event (increase in the stock price) does not mean that they have no knowledge or prior about the likelihood of this event.

[6] Prior work has identified four classes of conditions under which excess entry could be consistent with expected utility maximization. First, target markets may exhibit extreme skewness of distribution of rewards (Åstebro 2003). Second, entry may increase decision makers' utility independent of payoffs (e.g., through nonpecuniary benefits from independence/autonomy or from being one's own boss; Benz and Frey 2004). Third, excess entry may arise as a result of goal conflict in the principal–agent relationship (e.g., empire building by managers; Baker, Jensen, and Murphy 1988). Finally, expected failure may still be seen as optimal choice if decision makers anticipate that the learning (from failure) experience will maximize their lifetime chances of attaining the most beneficial trajectory (for an illustration, see Sarasvathy et al. 2013).

[7] The author interprets the results as a sign of overconfidence; however, there was no measure of the participants' beliefs about their performance or about their degree of confidence. A positive attitude toward ambiguity could produce the same empirical pattern.

[8] We thus elicited individual preferences by observing decision choices involving real monetary incentives. Incentivized tasks are broadly used and have been shown to "improve performance in easy tasks that are effort-responsive, like judgment" (Camerer and Hogarth 1999, p. 34).

[9] Both r_i and p_i can be thought of as market capacities because they reflect the percentage of participants who could obtain positive payoff. As an illustration, a game with a market capacity of 30% is a game (either chance- or skill-based) in which 30% of the participants could obtain a positive payoff.

[10] The video is available on request.

[11] We also elicited the participants' beliefs about their score and measured their corresponding willingness to bet (tasks C1–C3). These tasks are identical to tasks B1–B3, but the source of uncertainty is the participant's score instead of rank (see Table C1 in Online Appendix C). We also asked five questions to capture the shape of the utility function (task A2); a series of ANOVA test confirms the absence of any statistically significant difference between the three groups.

[12] This value is also referred to as "certainty equivalent" in some literature.

[13] We measured the participants' attitude toward ambiguity for skill-based games with a perceived likelihood of success of 12.5% and 87.5% because previous studies have found that people tend to be particularly risk taking when the probability is small and risk averse when the probability is high (see Tversky and Kahneman 1992).

[14] We examine only the neutral treatment group in order to ensure comparability with prior work in which participants did not receive any feedback on their performance. Our results for the treated groups are similar.

[15] All repeated-measures ANOVA tests are performed with errors clustered on the participant.

[16] We used the estimated score prior to receiving feedback.

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