Original Article

Biased Calibration: Exacerbating Instead of Mitigating Entrepreneurial Overplacement with Reference Values

Entrepreneurship Theory and Practice
2024, Vol. 48(5) 1131–1159

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DOI: 10.1177/10422587241227051
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Daniel Blaseg[1] and Armin Schwienbacher[2]

Abstract

Nascent entrepreneurs often believe that their chances of success are better than those of others due to imperfect information about the competencies and accomplishments of other entrepreneurs, leading to overplacement. Theory suggests that the provision of historical outcome data of comparable projects could help entrepreneurs develop more realistic plans and expectations by closing the information gap and enabling the calibration of their beliefs. However, effectively calibrating beliefs by incorporating new reference information requires effortful cognitive processing and rational integration of the data, which may be impeded by the same cognitive biases leading to overplacement initially. Drawing from a unique dataset that allows us to observe substantial parts of the planning process of 971 entrepreneurs, we investigate the effectiveness of providing reference values as a debiasing tool. Rather than rationally leveraging the information for honest self-assessment, our findings suggest that entrepreneurs use the information to differentiate themselves even more from the reference group after they see the historical values. This, in turn, results in an even higher level of overplacement.

JEL Classifications: G41, D91, L26, L25.

Keywords

overplacement, debiasing, crowdfunding, decision-making, entrepreneurship

Many entrepreneurial undertakings fail within the first years (Artinger & Powell, 2016; Cassar, 2014; Khelil, 2016; Stecanella, 2017). However, individuals continue entering entrepreneurship despite gloomy prospects and statistics (Hmieleski & Baron, 2009). Such

[1]Universitat Ramon Llull, ESADE Business School, Barcelona, Spain
[2]SKEMA Business School—Université Côte d'Azur, Euralille, Hauts-de-France, France

Corresponding Author:
Armin Schwienbacher, SKEMA Business School—Université Côte d'Azur, Avenue Willy Brandt, Euralille, Hauts-de-France 59777, France.
Email: armin.schwienbacher@skema.edu

excess market entry is often attributed to overplacement, a form of overconfidence in which individuals hold exaggerated beliefs of their own performance or abilities relative to others (Kraft et al., 2022; Moore & Healy, 2008). In other words, prospective entrepreneurs often believe that their chances of success are better than those of others.[1] Evidence indicates that overplacement occurs because of imperfect information individuals have about others (Moore & Healy, 2008) and is driven by cognitive errors in processing information (Kahneman & Tversky, 1995) and motivational accounts, such as the desire to view oneself positively (Brown, 2012). While a certain level of overplacement may be required to take on the risks of an entrepreneurial project and may also provide other benefits for the entrepreneur (e.g., deterring others from competing or improving social status; Van Zant & Moore, 2013), research in the field of entrepreneurship has mainly documented adverse effects resulting from overplacement, such as excess market entry and failure (Kraft et al., 2022). Overplacing individuals underestimate risk and competition (McCarthy et al., 1993), make more errors in judgment (Moore & Cain, 2007), and often spend less effort than required to create a competitive advantage due to perceived ease of competing (Cain et al., 2015; Camerer & Lovallo, 1999; Ng et al., 2009).

While several origins and consequences of overplacement are well established, the entrepreneurship literature is largely silent on potential remedies to mitigate overplacement (Zhang & Cueto, 2017). The lack of evidence is surprising, given the relevance of successful entrepreneurs to the economy and society (Shane, 2009). While unsuccessful entrepreneurial undertakings may also provide benefits on the micro (e.g., learning, sensemaking) and macro (e.g., release of knowledge) levels, failure comes with financial, social, and psychological costs for the individual and society (Ucbasaran et al., 2013), thus rendering initiatives intended to improve entrepreneurs' odds of success an important undertaking (Bergman & McMullen, 2022).

To avoid some of the pitfalls of overplacement, scholars (e.g., Hyytinen et al., 2014; Moore, 2020; Van Zant & Moore, 2013) and practitioners (e.g., Baer, 2018; McKinsey, 2019) recommend calibration to debias inflated beliefs. One potential way to achieve calibration is to analyze and consider historical outcomes of comparable projects as reference values (e.g., Hayward et al., 2006; Kahneman & Lovallo, 1993; Kahneman & Tversky, 1982).[2] Conceptually, considering representative performance statistics in the decision process should improve forecasts by taking exogenous scenarios into account (Flyvbjerg et al., 2009) and compensate for the gaps in information about others (Galesic et al., 2012). Calibration may also reduce overplacement by raising one's assessment of others (Krueger & Heck, 2021). Calibrating expectations with such reference values may help protect against disappointments in case of failure, thus providing psychological benefits (Logg et al., 2018), and could render confident beliefs more persuasive to others (Moore, 2020). Put simply, these scholars argue that providing entrepreneurs with better information about the performance of others is conceptually a simple remedy to mitigate overplacement, something which we plan to investigate empirically.

While the potential benefits of calibration are clearly articulated in the literature (e.g., Lovallo & Kahneman, 2003), little is known about the effectiveness of this approach and its limitations, from both an empirical and a theoretical standpoint. Consequently, often overlooked is the notion that the cognitive and motivational accounts leading to overplacement may also affect the process of calibration with reference values. In such cases, debiasing activities may even exacerbate the issue instead of enabling individuals to bypass the cognitive biases (Sanna et al., 2002), especially when the debiasing attempts require cognitive effort and rational processing of the information (Zhang & Cueto, 2017). In this study, we draw on theories of social comparison (Festinger, 1954) and self-enhancement (Alicke & Sedikides, 2009) to develop our theoretical arguments on why this approach is likely to backfire in reality. We argue that nascent entrepreneurs are likely to use the reference values to adjust themselves upward from the base rate, thus leading to even more overplaced beliefs. This effect results from cognitive errors in processing the reference values and the motivation to view themselves and their abilities positively. We then empirically test our conjectures on the impact of providing reference values in reward-based crowdfunding campaigns, which offer an apt context in which to conduct research on entrepreneurial decision-making and excess market entry. Existing studies indicate that three of four crowdfunding campaigns are intended to start a new business or to introduce a new product (Junge et al., 2022; Mollick & Kuppuswamy, 2014), but only one-third are successful in raising the requested amount (Cumming et al., 2020; Mollick, 2014; Piening et al., 2021). We use a self-developed online tool as the empirical setting to collect observations on entrepreneurial planning before a possible crowdfunding campaign. This setup allows us to observe a substantial part of the planning process and the use of reference values of 971 nascent entrepreneurs over time.

Our study offers several results. We find that entrepreneurs who use the actual historical reference value in their planning process tend to adjust their estimates significantly upward, further away from the disclosed reference values. Thus, rather than leveraging reference values for honest self-assessment, these entrepreneurs use the provided information to account for their belief that they are better than others, leading them to an even higher level of overplacement than before they knew the reference values. However, not all individuals react in the same way. Nascent entrepreneurs with higher levels of education and occupational experience not only are less likely to make use of reference values but also exhibit larger upward adjustment tendencies when provided with reference values. These two findings lend further support to our theoretical framework by indicating that the cognitive and motivational accounts associated with overplacement actually impede the intended debiasing process of calibration with reference values.

Our study adds to recent discussions and calls for research on overplacement and debiasing (e.g., Gutierrez et al., 2020; Zhang & Cueto, 2017) by investigating when and how prospective entrepreneurs make use of contextual information to calibrate their beliefs and the effectiveness of this approach as a debiasing device. We contribute to the scarce literature on debiasing by showing that the effectiveness of debiasing activities depends on the ability to bypass the underlying processes leading to the bias. By doing so, we extend our understanding of the origins of overplacement. As Kraft et al. (2022) note, overplacement appears to be the least researched aspect of overconfidence in the entrepreneurship literature—particularly in the prelaunch phase. Our study fills this gap and extends current knowledge on the role of overplacement in entrepreneurship. Our findings question the provision of reference values to entrepreneurs; we show that they significantly overinflate their estimates when reference values are provided to them. Understanding how overplacement due to the provision of reference values is associated with entrepreneurial thinking and actions provides the basis for influencing those processes. The plain provision of reference values during the planning process may not encourage entrepreneurs to develop more realistic expectations of new business performance and may not debias entrepreneurial overplacement as intended. We discuss several suggestions based on our findings that may help leverage the conceptual benefits of calibration with reference values.

In addition, our study adds to the growing literature on entrepreneurial planning and decision-making. Recent research (e.g., Amore et al., 2021) shows that entrepreneurs are subject to cognitive biases that impede learning from performance feedback. By contrast, we shed light on the pre-entry process by focusing on belief updating based on debiasing activities with contextual information that usually precedes actions for which performance feedback can be obtained (Bennett & Chatterji, 2023). The failure to update beliefs is most critical in the earliest phases of entrepreneurial activities, as it influences the subsequent choice of starting to become an entrepreneur in the first place as well as later performance (Chen et al., 2018). Thus, knowing when and how prospective entrepreneurs use reference values is crucial for better understanding entrepreneurial decision-making in the pre-entry stage.

Literature and Hypotheses Development

Overplacement

Cognitive biases in decision-making are a widespread phenomenon in entrepreneurship (Astebro et al., 2014; Busenitz & Barney, 1997; Kraft et al., 2022; Shepherd et al., 2015; Zhang & Cueto, 2017). Whereas cognitive biases can be beneficial in some circumstances (e.g., by increasing the motivation to initiate entrepreneurial action; see Simon & Shrader, 2012), the view of biases as systematic errors in decision-making is more established, thus leading to a plethora of documented negative consequences (e.g., increased likelihood of failure; see Hayward et al., 2006). One important cognitive bias is overconfidence, which describes several distinct constructs that measure inflated views of the self (Logg et al., 2018). Depending on the benchmark with which beliefs are compared, Moore and Schatz (2017) differentiate among three forms of overconfidence: (1) overestimation (significant and positive differences in ex ante beliefs vs. ex post outcomes), (2) overprecision (excessive confidence in the accuracy of own beliefs), and (3) overplacement (significant and positive difference in beliefs about own performance or abilities relative to others'). Researchers commonly assume that the distinct types of overconfidence share the same psychological underpinnings (e.g., Cooper et al., 1988), but recent findings challenge this assumption (Moore & Healy, 2008). As conceptually and empirically distinct measures, overestimation, overprecision, and overplacement can even be negatively correlated with each other in real life (Cain et al., 2015; Kraft et al., 2022). However, Moore and Healy's (2008) differential information theory provides a common ground: individuals often have imperfect information about their own abilities but even worse information about those of others. The lack of relevant information about others is particularly important in the case of overplacement, as it requires a direct comparison with a reference group.

While overplacement appears to be the least researched aspect of overconfidence in the entrepreneurship literature, it is a crucial factor in understanding the entrepreneurial process. Kraft et al.'s (2022) recent meta-analysis on the effects of the different forms of overconfidence in different entrepreneurial phases suggests a negative relationship among overplacement, market entry (e.g., Camerer & Lovallo, 1999), and venture performance (e.g., Wu & Knott, 2006) due to excessive risk-taking (e.g., McCarthy et al., 1993), errors in judgment (Moore & Cain, 2007), and competitive blind spots (Ng et al., 2009). Gutierrez et al. (2020) and Cain et al. (2015) provide further insights into the link between overplacement and excess market entry by demonstrating that overplacement predominantly affects and drives selection into skill-based and competitive markets.

The underlying mechanisms leading to overplacement are well-established in the literature (Zell et al., 2020) and commonly classified into cognitive and motivational accounts. While both explanations have received empirical support (e.g., Brown, 2012; Chambers &

Windschitl, 2004) and share similar psychological roots, methodological dissimilarities in how they are assessed have resulted in differences in their theoretical attribution (Logg et al., 2018). The cognitive explanation, rooted in social comparison theory, mainly builds on errors in the representation or processing of information (Kahneman & Tversky, 1995). The most relevant argument, egocentrism, captures the tendency of individuals to overweight their own characteristics and underweight the characteristics of the reference group. While egocentrism may occur rationally because individuals simply know more about themselves than about others (Moore & Healy, 2008), the focus on the self leads to overplacement. Individuals then self-select the evaluative dimensions they consider relevant and in which they perceive themselves favorably (Kruger, 1999; Zell & Alicke, 2011). The disproportionate influence of self-relevant information can also be traced to differences in the accessibility of information regarding the comparison group (Chambers & Windschitl, 2004). A closely related notion is "base rate neglect," or the tendency of individuals to ignore reference values in favor of information on the self, thus leading to overplacement. Typically, this is because individuals tend to see themselves as too unique to be compared (Bar-Hillel, 1980; Kahneman & Lovallo, 1993).

Research in social psychology ties overplacement to motivational accounts, such as the desire for positive self-beliefs, self-enhancement, and self-protection (Alicke & Sedikides, 2009; Chambers & Windschitl, 2004; Sedikides & Alicke, 2019). Put simply, individuals attempt to bolster their self-concepts by appraising themselves and their abilities more positively than they appraise others and their abilities. Going beyond satisfying the desire to promote and maintain a superior self-image, higher levels of overplacement also enable individuals to justify their choice to themselves (Ronay et al., 2017) and to attain higher status, as others often perceive overplacing individuals as more competent (Anderson et al., 2012).

In this study, we focus on overplacement and define it as exaggerated beliefs of one's performance or abilities relative to others' (Benoît et al., 2015; Krueger & Heck, 2021; Moore & Healy, 2008). Given the importance of entrepreneurs to the economy and society on the one hand and the mostly negative consequences of overplacement on the other hand, understanding which activities and instruments can help entrepreneurs develop more realistic expectations is critical. Such instruments will then help improve and influence the quality of entrepreneurial entry and subsequent performance.

Calibration with Reference Values

According to Moore and Healy (2008), overplacement is often caused by a lack of representative information about others that allow benchmarking and calibration. Providing entrepreneurs in the pre-entry stage with context-dependent information, such as the historical outcomes of comparable projects, is thus often discussed by scholars (e.g., Hyytinen et al., 2014; Moore, 2020; Van Zant & Moore, 2013) and practitioners (e.g., Baer, 2018; McKinsey, 2019) as a potential remedy to debias entrepreneurial overplacement by closing the information gap. In general, calibration involves the appropriateness of estimates (Keren, 1991; Lichtenstein et al., 1982). In the case of overplacement, it describes the process of considering outcome statistics of comparable past projects to benchmark own estimates (Van Zant & Moore, 2013). Conceptually, being aware of historical statistics on competitors' failure rates should help entrepreneurs calibrate their beliefs about the expected likelihood of success in starting an entrepreneurial project by developing realistic plans and expectations. Considering past statistics in the planning process can help improve forecasts by taking unforeseen scenarios and external aspects into account (Kahneman & Lovallo, 1993). As the planned undertaking shares some of the environmental attributes with comparable ventures, the historical failure rate of competitors should be, at least to some extent, indicative of the own initiative's likelihood of success when the sample size is large and representative (Simon & Shrader, 2012). Extreme past events cancel each other out, rendering the mean of a representative sample often a reasonable representation of the outcome to be expected. Having a better sense of the underlying statistics, what could happen, and what one could reasonably expect may encourage entrepreneurs to think about whether the confidence in their own abilities is actually warranted for making the project successful or whether adaptations are required. This view is consistent with entrepreneurial learning based on information economics in that the arrival of new, relevant information should induce entrepreneurs to update their beliefs about ultimate performance and make more informed decisions (Politis, 2005). Calibration with reference values is also closely related to the concept of "taking the outside view" (Kahneman & Lovallo, 1993). The outside view builds on the predictive properties of reference values as a representative statistic, requires ignoring the idiosyncratic details of the own project, and avoids forecasting any scenario of the future course of action with these details. Instead, the individual examines the outcomes of a class of similar projects and then positions the current project within the distribution of outcomes for the chosen reference class. Thus, considering historical failure rates should help entrepreneurs calibrate their beliefs in the planning phase. Given that entrepreneurs often have overplaced beliefs due to imperfect information about others, providing reference values should, according to this view, result in the rational adjustment of inflated self-judgments toward the more representative reference value if the entrepreneurs deliberately process the new information in an unbiased manner (Zell et al., 2020).

Despite the conceptual benefits, the direct effect of providing reference values as a potential remedy to mitigate entrepreneurial overplacement remains poorly researched. However, at least two studies provide insights into the circumstances of providing reference values to entrepreneurs. Hyytinen et al. (2014) show that entrepreneurs have difficulties coming up with a representative reference group. Barbosa et al. (2019) find that the framing of anchoring points regarding critical events necessary for the completion of an entrepreneurial undertaking (positively framed as high success probability and negatively framed as low failure probability) can exert differential impacts on entrepreneurs' estimated odds of success. Hayward et al. (2006) advance a hubris theory of entrepreneurship to explain why so many entrepreneurs choose to enter but subsequently fail. In discussing the question of why entrepreneurs start projects in light of low objective likelihoods of success, they state that how entrepreneurs use information such as reference values in the preentry period and its effect on overplacement is an important but open empirical question.

Effectiveness of Mitigating Overplacement with Reference Values

The debiasing literature (e.g., Larrick, 2004) notes that debiasing activities may even exacerbate an issue instead of enabling individuals to bypass the cognitive biases (Sanna et al., 2002), especially when the debiasing attempts require cognitive effort (Zhang & Cueto, 2017). As Fischhoff (1982, p. 431) states: "a debiasing procedure may be more trouble than it is worth if it increases people's faith in their judgmental abilities more than it improves the abilities themselves." We further develop this notion and argue that the effectiveness of debiasing activities depends on the ability to bypass the underlying processes leading to the bias. Our theoretical arguments consider both cognitive and motivational accounts for overplacement and show that this condition is not fulfilled in the case of calibration with reference values to mitigate overplacement, and thus, this approach may backfire.

To unleash the conceptual benefits of calibration with reference values, considering such values in the decision process is a first step. As discussed previously, the neglect of reference values may contribute to overplacement. While several studies casually suggest a natural tendency of individuals to ignore reference values (e.g., Kahneman & Lovallo, 1993), this issue can be linked to individual differences and the cognitive and motivational accounts leading to overplacement. A central perspective of the motivational account is the desire for positive self-beliefs and self-enhancement. Thus, individuals will engage in activities that help bolster their self-beliefs and avoid them when new information could threaten this perception. The positive image of oneself as a capable entrepreneur who is leading a project to success may be negatively affected when the reference values are similar to the own estimate of success, indicating that own abilities are likely not contributing much to the odds of success as expected. When estimating the chance of success, entrepreneurs incorporate an assessment of their abilities to successfully establish the venture (Kickul et al., 2009). The assessment of own abilities and the link to success is typically represented by the notion of entrepreneurial self-efficacy (Bandura, 1977; McGee et al., 2009), which can significantly increase an entrepreneur's opportunity confidence (Dimov, 2010). Entrepreneurial self-efficacy mainly derives from past experiences that provide opportunities for mastery experiences and vicarious learning (Zhao et al., 2005). As such, aspects of human capital, and especially industry experience and education, are the most prominent drivers (Newman et al., 2019). Given the motivational account of overplacement, entrepreneurs with a higher level of entrepreneurial self-efficacy, as proxied by industry experience and education, are less likely to make use of reference values, as doing so could threaten their positive self-perception. The cognitive accounts provide further arguments for why entrepreneurs with higher levels of human capital may be less inclined to use reference values. With an ego-centric focus on the dimensions on which they perceive themselves favorably, they are often prone to think that they are too unique to make use of past statistics as they believe that others do not possess the same capabilities or at least not to the same extent. Given these arguments, we hypothesize the following:

> *Hypothesis 1:* Entrepreneurs with higher levels of (a) industry experience and (b) education are more likely to ignore aggregated reference values on outcomes of comparable entrepreneurial initiatives.

Conditional on the use of reference values, the effectiveness of calibration with reference values depends on how entrepreneurs make use of it. Again, the motivational and cognitive accounts associated with overplacement are likely to impede rational implementation.

Individuals frequently engage in social comparison to assess their abilities, opinions, and beliefs against those of peers (Buckingham & Alicke, 2002). The process of thinking about information about others in relation to the self affects their self-concept and might lead to a change in self-evaluation, affect, or behavior, depending on the existence of similarities or differences between themselves and the reference group (Gerber et al., 2018; Wood, 1996). A plethora of studies on social comparison suggests that in a setting in which the reference value is worse off than the comparer, self-evaluation may move away from the reference value and becomes more positive (Gerber et al., 2018). As statistics on start-up failure rates are usually lower than entrepreneurs' beliefs about their chances, this stream of research offers a solid framework for our setting.

As the desire for such positive self-regard is assumed to be a universal human trait, individuals employ various strategies to promote and maintain a positive image of themselves. When comparing themselves with reference values, individuals egocentrically infer that their dispositional qualities or ability exceed those of others and focus on idiosyncratic and self-serving criteria that put them in a more favorable light than others, thus confirming the biased perception to be better than the base rate (Alicke et al., 1995; Alicke & Govorun, 2005). To account for their beliefs of being better than others, individuals adjust themselves upward from the average, which then leads to an even more overplaced belief (Moore & Cain, 2007). Thus, rather than helping entrepreneurs overcome the myopic focus on the self in the planning process, these theoretical conjectures—if translated into overplacement—suggest that providing reference values to entrepreneurs may even exacerbate their overplaced beliefs and thus lead to even higher levels of overplacement.

Hypothesis 2: Providing information on aggregated reference values on outcomes of comparable entrepreneurial initiatives leads entrepreneurs to adjust their expectations of individual performance upward.

However, similar to our arguments in Hypothesis 1, individual differences, especially those related to entrepreneurial self-efficacy, may be important factors explaining the implementation of reference values. For example, in line with the cognitive account, individuals with higher levels of capabilities known to positively affect venture success often hold unrealistic beliefs about the relevance of their own skills while discounting the skills of others (Chambers & Windschitl, 2004; Forbes, 2005). These beliefs may lead them to attend to reference values less often in the first place but may exacerbate their myopic focus if they do so. To justify their positive self-perception and the relevance of the evaluative dimensions, entrepreneurs with higher levels of human capital are likely to differentiate themselves more clearly from the base rate, thus leading to even more overplaced beliefs. Again, building on the well-established insights from the literature on entrepreneurial self-efficacy (e.g., Newman et al., 2019), we expect entrepreneurs with higher levels of educational attainment and occupational experience to exhibit upward adjustment tendencies as they believe that their experience provides them with a competitive advantage. Thus:

Hypothesis 3: Entrepreneurs with higher levels of (a) industry experience and (b) education are more likely to adjust their expectations of individual performance upward when provided with aggregated reference values on outcomes of comparable entrepreneurial initiatives.

Taken together, we expect that the cognitive and motivational accounts leading to overplacement may also affect the use of calibration, which ultimately exacerbates the issue instead of enabling individuals to bypass the cognitive biases. Next, we empirically test these theoretical conjectures.

Empirical Setting: Crowdfunding Calculator

Our unique data come from the website called the *Crowdfunding Calculator* (for screenshots of the different web pages, see Web Appendix A), a free online tool in the area of crowdfunding that helps nascent entrepreneurs considering a reward-based crowdfunding campaign to calculate expected profits of their project as a way to guide them in their decision on whether to eventually launch a campaign. The tool provides an easy-to-use online interface and a step-by-step guide to preparing a professional crowdfunding budget that includes a wide range of possible fixed and flexible costs. We asked the nascent entrepreneurs to provide estimates on the planned setup of their campaigns, including the funding goal, reward prices, development, production, and shipping costs, as well as an estimated probability of successfully raising the requested funds.

After providing these numbers, the entrepreneurs had the opportunity to obtain information on historical success probabilities of comparable projects from an internal database containing more than 665,000 crowdfunding campaigns across several platforms and 30 different project categories (i.e., they could click on a button, but they were not obliged to continue). Following research on crowdfunding, we define success as reaching the funding goal (e.g., Mollick, 2014), which is rooted in the all-or-nothing mechanism that most crowdfunding platforms employ (Cumming et al., 2020). This dichotomous metric provides an unambiguous outcome indicator of whether the project can be realized or not and can be compared across projects. The reference values provide entrepreneurs with the percentage of campaigns that reached the funding goal, adjusted for platform and category choice. This setting allows us to compare initial subjective estimates of success with historical outcomes of similar campaigns as a representative benchmark. We can further observe whether entrepreneurs take this information into account when using the calculator in any subsequent trial, as they again needed to provide an estimated probability of success. Most entrepreneurs used the calculator several times in a row, so we can discern how they changed these probabilities over time. We adjusted all the values provided to users for the individual platform and category choice (which they need to report at the beginning of the calculation) so that the data are comparable to the entrepreneur's planned undertaking using the calculator.[3] At the end of each round of calculation, the entrepreneur received an extensive scenario-based overview of the timing and amount of the respective aggregated costs and how much profit or loss the campaign was expected to generate. The tool was available in different languages and allowed for iterations with different estimates.

Data and Summary Statistics

Our data period was from May 2016 to October 2017. Sophisticated tracking based on cookies and fingerprints of web browsers enabled us to identify 1,682 unique nascent entrepreneurs from 26 countries who used the Crowdfunding Calculator. The tool was promoted through press coverage on several entrepreneurship-related blogs and magazines and recommendations from entrepreneurship associations to reach a broad and representative audience. Moreover, paid advertising on search engines and social media platforms, as well as first-page ranks on Google for important keywords such as "crowdfunding profitability" or "crowdfunding planning," ensured a vast reach. Of the total users, 223 did not complete at least two full calculations, 83 users provided systematic and nonmeaningful answers (such as 0 for every input), and 74 users provided values of their estimated success probability after using reference values.[4] These observations are not included in the analyses. To supplement the data with information on user demographics and their projects (if they started them), we contacted all users 6 months after their last usage via email and asked them to answer a survey. We received agreement from 74.5% of the users.[5]

Our final sample comprises information on a substantial part of the planning process of 971 nascent entrepreneurs who used the calculator at least twice and answered the survey. Of these, 428 launched a campaign. The calculations made with the tool predicted, on average, an expected profit of roughly $7,300 per campaign. Furthermore, the entrepreneurs expected to receive funding of $45,000, on average, with a probability of 62.5%. These values are fairly high compared with the historical average funding of $12,000 and the historical average funding probability of 40%.

In line with the literature on overplacement (e.g., Moore & Healy, 2008; Kraft et al., 2022), we operationalize our empirical measure of *Overplacement* as the difference between the expected probability of success given by the entrepreneurs in their calculation and the respective historical reference value. The reference value is the average success rate of all previously undertaken reward-based crowdfunding campaigns run in the same project category and on the same platform, as reported by the entrepreneurs during the use of the Crowdfunding Calculator. A positive value for *Overplacement* means that the respective entrepreneurs estimated their probability of success above the reference value. As entrepreneurs can use the calculator more than once, we calculate a value of this measure for the first and last use, which we call *Overplacement (Start)* and *Overplacement (End)*, respectively. Users in the sample are only able to obtain reference values after providing their own estimates. This ensures that *Overplacement (Start)* is always unaffected by reference values. However, users could request them every time they use the calculator.

Although overplacement represents a widespread cognitive bias that affects many individuals, several scholars have shown that some individuals exhibit higher levels of overplacement than others. Because overplacement can be due to differences in personal experience, we expect individual factors also to affect the handling of reference values. To capture a creator's familiarity with crowdfunding norms and culture (e.g., Huang et al., 2022), we control for the possible effects resulting from differences in experience with crowdfunding as an initiator and backer (e.g., Blaseg et al., 2020). Entrepreneurs with more experience in crowdfunding might also be more aware of historical success statistics in the field and, thus, more or less likely to use reference values.[6] Also, we add control variables for demographics such as gender and age (Forbes, 2005), employment status and intention of starting a business (Koellinger et al., 2007), and the time and effort spent in venture planning (Townsend et al., 2010). These control variables capture differences in individual risk perceptions and ensure that the effect stems from differences in information processing rather than individual private knowledge (Barbosa et al., 2019). Table B3 in Web Appendix B summarizes the definitions of all variables.

Tables 1 and 2 present the basic summary statistics of our variables. Table 1 shows statistics for the full sample, and Table 2 shows differences between the sample of entrepreneurs who used and who did not use the reference values. On average, entrepreneurs systematically overplace their chances of success, independently of knowing the historical probability of success for similar projects. While we are not the first to observe the presence of overplacement among nascent entrepreneurs, this finding is important to establish before assessing the effect of providing reference values on overplacement. Entrepreneurs estimate their probability of having a successful crowdfunding campaign to be 57.5%, while the historical reference value is 38.0% (adjusted for the choice of platform and project category). In our sample, 91.9% of the entrepreneurs consider themselves "above average"; that is,

Table 1. Descriptive Statistics for Full Sample.

	Total					
Variable	*n*	Mean	*SD*	Median	Min	Max
Use of reference values (1 = yes)	971	0.545	0.498	1.000	0.000	1.000
Overplacement (Start)	971	19.506	15.439	19.000	−31.000	60.000
Overplacement (End)	971	24.495	22.888	24.000	−35.000	80.000
Start of campaign (1 = yes)	971	0.441	0.497	0.000	0.000	1.000
Success of campaign (1 = yes)	428	0.381	0.486	0.000	0.000	1.000
Gender (1 = female)	971	0.299	0.458	0.000	0.000	1.000
Education (1 = university degree)	971	0.516	0.500	1.000	0.000	1.000
Job status (1 = open for change)	971	0.425	0.495	0.000	0.000	1.000
Industry experience (in years)	971	8.476	4.326	8.000	0.000	26.000
Age (in years)	971	31.766	5.602	31.000	20.000	56.000
Crowdfunding reason (1 = commercial)	971	0.591	0.492	1.000	0.000	1.000
Number of calculations	971	10.452	5.288	10.000	2.000	24.000
Backer experience (1 = yes)	971	0.673	0.470	1.000	0.000	1.000
Initiator experience (number of campaigns)	971	0.262	0.645	0.000	0.000	9.000
Time span between calculations (in days)	971	22.563	14.839	21.000	0.000	85.000
Relative change in funding amount	971	−0.093	0.297	−0.091	−0.608	0.406
Traffic source (1 = organic/direct visit)	971	0.391	0.488	0.000	0.000	1.000

they estimate their chances of success higher than the historical average outcome of comparable projects in the same project category and on the same platform. As Table 1 shows, entrepreneurs overplace their probability of campaign success by 19.5 percentage points when using the calculator the first time and by 24.5 percentage points when they use it last. In addition, 54.5% of the entrepreneurs used the reference values at least once in their calculations, while the remaining 45.5% never used them at any time. On average, entrepreneurs used the calculator 10.5 times (with a median of 10) and a time span of 22.6 days between the first and last usage. Moreover, they lowered the requested funding amount between the first and last round of calculation by approximately 9 percentage points (though this difference is not statistically significant).

Table 1 further shows the characteristics of the entrepreneurs. Here, 30% of the entrepreneurs are female, 52% have a university degree, 43% are open to a change in their current employment situation, and the average entrepreneur has more than 8 years of relevant industry experience. Moreover, 59% of the entrepreneurs reported that they are planning a crowdfunding campaign for commercial purposes, 67% have already backed another crowdfunding project, and 26% already have experience in crowdfunding as a project initiator.

Table 2 shows that 529 of the 971 users used the reference values. Those who used them have significantly higher *Overplacement (End)* values. Indeed, they overplace their chances by 9 percentage points more than entrepreneurs who never saw the reference values (28.6% vs. 19.6%). Reference values tend to be used less often by experienced and more educated users as well as by those planning a campaign for a commercial project (vs. a social or artistic project). Moreover, users with crowdfunding experience and women are more likely to use reference values.

Table 3 provides insights into the impact of using reference values. In the first columns (without propensity score matching), we calculate the difference between *Overplacement*

Table 2. Descriptive Statistics by the Use of Reference Values.

	No use of reference values						Use of reference values						
Variable	*n*	Mean	*SD*	Median	Min	Max	*n*	Mean	*SD*	Median	Min	Max	Difference in means
Overplacement (Start)	442	18.683	16.261	18.500	−31.000	60.000	529	20.193	14.698	20.000	−19.000	56.000	1.510
Overplacement (End)	442	19.561	18.060	19.000	−35.000	71.000	529	28.618	25.546	27.000	−35.000	80.000	9.057***
Start of campaign (1 = yes)	442	0.394	0.489	0.000	0.000	1.000	529	0.480	0.500	0.000	0.000	1.000	0.086***
Success of campaign (1 = yes)	174	0.494	0.501	0.000	0.000	1.000	254	0.303	0.461	0.000	0.000	1.000	−0.191***
Gender (1 = female)	442	0.265	0.442	0.000	0.000	1.000	529	0.327	0.470	0.000	0.000	1.000	0.062**
Education (1 = university degree)	442	0.561	0.497	1.000	0.000	1.000	529	0.478	0.500	0.000	0.000	1.000	−0.083**
Job status (1 = open for change)	442	0.464	0.499	0.000	0.000	1.000	529	0.393	0.489	0.000	0.000	1.000	−0.071**
Industry experience (in years)	442	8.916	4.105	9.000	0.000	24.000	529	8.108	4.473	8.000	0.000	26.000	−0.809***
Age (in years)	442	32.244	5.300	32.000	22.000	56.000	529	31.367	5.816	31.000	20.000	55.000	−0.878**
Crowdfunding reason (1 = commercial)	442	0.661	0.474	1.000	0.000	1.000	529	0.533	0.499	1.000	0.000	1.000	−0.128***
Number of calculations	442	9.688	5.050	9.000	2.000	24.000	529	11.091	5.401	11.000	2.000	24.000	1.403***
Backer experience (1 = yes)	442	0.536	0.499	1.000	0.000	1.000	529	0.786	0.410	1.000	0.000	1.000	0.250***
Initiator experience (number of campaigns)	442	0.204	0.808	0.000	0.000	9.000	529	0.310	0.463	0.000	0.000	1.000	0.106**
Time span between calculations (in days)	442	24.118	15.172	22.000	1.000	85.000	529	21.265	14.442	20.000	0.000	79.000	−2.853***
Relative change in funding amount	442	−0.086	0.285	−0.088	−0.585	0.390	529	−0.098	0.306	−0.091	−0.608	0.406	−0.012
Traffic source (1 = organic/direct visit)	442	0.281	0.450	0.000	0.000	1.000	529	0.484	0.500	0.000	0.000	1.000	0.203***

$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

Table 3. Difference-in-Differences Estimation.

	Without PSM		With PSM	
Variable	Nonusers of RV	Users of RV	Nonusers of RV	Users of RV
Overplacement (Start)	18.683	20.193	21.043	21.769
Overplacement (End)	19.561	28.618	22.015	30.295
Difference in means	0.878**	8.425***	0.972**	8.526***
SE	(0.355)	(0.769)	(0.429)	(1.038)
Difference-in-differences	7.548***		7.554***	
SE	(0.902)		(1.123)	

Notes. PSM = propensity score matching; RV = reference values. Nearest-neighbor matching without replacement is used for matching using all known precalculation characteristics. Descriptive statistics of the variables used for matching are provided in Table B3 in Web Appendix B. While entrepreneurs show significant differences in characteristics before PSM, the Hotelling test of equal vector means provided in Table B4 reveals no significant differences between users and nonusers of reference values PSM, indicating successful matching. The results are qualitatively and quantitatively robust to the use of coarsened exact matching.
***$p < .01$, **$p < .05$, *$p < .1$.

(End) and *Overplacement (Start)* for both subgroups (those who used reference values and those who did not). We then take the difference between these two differences (akin to a difference-in-differences design), which yields a value of 7.5 percentage points. This value is statistically significant at the 1% level and indicates that entrepreneurs using the reference values significantly increase their level of overplacement compared with nonusers. To account for potential pretreatment differences and increase the plausibility of the parallel trends assumption underlying the difference-in-differences approach (Roth et al., 2023), we present the same calculations but with users matched on all known precalculation characteristics extracted from the questionnaire (e.g., experience, gender) in the right-hand columns.[7] We obtained qualitatively and quantitatively similar results with an average treatment effect on the treated of 8.28 percentage points.

A crucial aspect of providing reference values is the choice of a suitable class of reference cases. The reference class must be large enough to be statistically meaningful but narrow enough to be fully comparable to the specific undertaking. While the average number of reference values in our dataset is determined by users' choice of platform and category and ranges from 1,328 to 119,850 campaigns (Median: 9,215), entrepreneurs might doubt the comparability of their undertaking to these broad classes. Thus, we test the robustness of our results to different reference classes, which vary in size and the level of comparability, in separate data collections and time frames. In the first alternative, we provided users with the average outcome of the 100 most comparable projects. In the second alternative, only the outcomes of the 10 most comparable projects with disclosed campaigns' names were shown. Comparability of projects is based on propensity scores using platform and category choice, as well as funding goal and timing. The results are qualitatively and quantitatively similar to the provision of the complete reference class (see Table B5 in Web Appendix B).

Analyses

To perform our analysis, first, we examine the individual characteristics related to self-efficacy affecting the decision to use reference values. This analysis allows us to test

Hypothesis 1. Second, we investigate whether the use of reference values, conditional on the use of reference values, affects overplacement to test Hypotheses 2 and 3.

Determinants of Using Reference Values and Final Overplacement

The design of the calculator and the descriptive results from Tables 2 and 3 suggest that the decision of individuals to use reference values may not be random. To control for the endogenous nature of using reference values and to disentangle the impact of using reference values on overplacement, we employ a simultaneous equations model with endogenous switching using full information maximum likelihood (FIML) estimation. This method is a generalized version of the traditional Heckman model and accounts for unobservable factors related to the decision to use reference values (Heckman, 1979; Maddala, 1983).

We estimate an endogenous switching regression model using FIML estimation,[8] which consists of a binary selection equation and two outcome equations on the variable of interest, in this case overplacement. Formally, we have

$$I_i^* = \gamma' Z_i + \varepsilon_i \text{ with } I_i = \begin{cases} 1 \text{ iff } I_i^* > 0 \\ 0 \text{ iff } I_i^* \leqslant 0 \end{cases} \tag{1}$$

$$\gamma_{i0} = \beta_0' X_i + u_{i0} \text{ if } I_i = 0 \tag{2a}$$

$$\gamma_{i1} = \beta_1' X_i + u_{i1} \text{ if } I_i = 1. \tag{2b}$$

Equation (1) is the latent selection equation, estimated by a probit model. Here, I_i equals 1 if and only if the individual uses the reference values. Equation (2a) analyses overplacement after using reference values while controlling for selection effects, and equation (2b) does the same for individuals that do not use reference values. Next, γ_{ji} are the dependent variables in the outcome equations that correspond to overplacement; X_i and Z_i are vectors of independent variables; β_0, β_1, and γ are vectors of the parameters, and ε_i and u_{ji} are error terms assumed to have a trivariate normal distribution. With this joint normality assumption, we can use FIML estimation to fit the model and obtain consistent standard errors (Lee & Trost, 1978). The vector Z_i in the selection equation (1) does not need to be different from the X_i vectors of independent variables in equations (2a) and (2b) for the purpose of identification (Vella & Verbeek, 1999); thus, we control for all observed individual-level characteristics, such as crowdfunding experience, gender, and age; usage-driven characteristics, such as the number of calculations and reasons for use; and platform and category fixed effects. While the model could be identified by nonlinearities, we include an exogenous variable as an exclusion restriction in the selection equation. While the validity of exclusion restrictions remains a statistically untestable assumption (Kiviet, 2017; Lewbel, 2019), the specification even of weakly correlated covariates helps ensure that the model is not only identified on the basis of the nonlinearities of the probit model. Thus, we include an exclusion restriction in the first stage that is correlated with the decision to use reference values but is not correlated with the outcome—namely, the traffic source of visitors to the Crowdfunding Calculator. We code direct and referred visits as 1 and all other sources (i.e., organic and paid sources) as 0. Direct and referred visitors may have read about the tool's existence in entrepreneurship-related blogs and magazines or were referred from entrepreneurship associations. These users may be more aware of the different features of the tool and, thus, more likely to use the reference values. At the same time, we do not expect any direct effect on the final level of overplacement, as the groups of directed/referred and organic/paid users were actively looking for support in preparing a campaign, either by reading relevant media articles or by searching information on the internet. The inclusion of this exogenous variable helps ensure that the model is well identified and increases the reliability of our estimates.

However, to ensure that our results are not driven by the choice and strength of the exclusion restriction, we follow Park and Gupta (2012) and Schweidel and Knox (2013) and employ an instrument-free estimation approach using Gaussian copulas. Gaussian copulas capture the correlation between the endogenous variable and the error term by modeling their joint normal distribution on the basis of the observed data and do not require the inclusion of an instrumental variable (Rossi, 2014). The model generates consistent parameter estimates even when the assumed normal distribution of the error term is not present (Park & Gupta, 2012). The results reinforce the robustness of our main specification (see Table B6 in Web Appendix B).

Finally, we use the model estimates from the second-stage regression equations (2a) and (2b) in a counterfactual analysis to assess the difference in overplacement between users and nonusers of reference values. We compute the hypothetical overplacement for users if they would not have used reference values, which we obtain by plugging the vector of individual characteristics for the subsample of users of reference values into the second-stage regression estimates of nonusers. We repeat this step for nonusers to obtain their hypothetical overplacement value. To infer the magnitude of using reference values, we compute the following differences between the actual and the hypothetical overplacement for users using equation (3a) and nonusers using equation (3b):

$$\underbrace{y_{1i}}_{\text{actual}} - \underbrace{E[y_{2i}|I_i>0]}_{\text{hypothetical}} \tag{3a}$$

$$\underbrace{y_{2i}}_{\text{actual}} - \underbrace{E[y_{1i}|I_i>0]}_{\text{hypothetical}}. \tag{3b}$$

The first term in equations (3a) and (3b) is the actual overplacement of a user/nonuser of reference values, and the second is the hypothetical overplacement that would be obtained by the same individual had he or she not used/used the reference values. The difference explicitly quantifies the impact of using reference values on overplacement and allows us to disentangle the effect of using reference values by different levels of initial overplacement.

The first column of Table 4 presents the results on the determinants of using the proposed reference values. Reported values are marginal effects. In line with Hypothesis 1, we find that users with more industry experience are less likely to use reference values, as are users with a higher level of education. These results suggest that these users believe they do not need this information or avoid it as a potential threat to their self-perception and lend support to our theoretical arguments regarding the cognitive and motivational underpinnings.

Table 4 further examines the determinants of overplacement based on the endogenous switching model. The dependent variable in the last two columns is *Overplacement (End)*. The first column is the first-step equation of the endogenous switching model. Controlling for the endogenous choice of requesting reference values, we find that entrepreneurs tend to increase their estimation even more if they use the reference values, as the coefficient is greater than 1 and statistically significant from 1 at the 1% level (coefficient of 1.342, which is significantly different from 1 at $p = .000$). By contrast, entrepreneurs who do not use the reference values tend to use similar values in their last calculation to those in their first

Table 4. Determinants of Overplacement (End).

	Probit (marginal effects)	Endogenous switching	
Variables	Determinants of using reference values	Use of reference values	No use of reference values
Overplacement (Start)	0.001	1.342***	0.950***
	(0.001)	(0.051)	(0.030)
Gender (1 = female)	0.071**	−3.725**	−2.207**
	(0.031)	(1.522)	(0.867)
Education (1 = university degree)	−0.066**	3.099**	1.714**
	(0.029)	(1.476)	(0.747)
Job status (1 = open for change)	−0.076**	1.353	0.967
	(0.030)	(1.496)	(0.762)
Industry experience (in years)	−0.011***	0.494**	0.365***
	(0.004)	(0.238)	(0.108)
Age (in years)	−0.001	−0.080	−0.119
	(0.003)	(0.176)	(0.074)
Crowdfunding reason (1 = commercial)	−0.109***	3.574**	1.816**
	(0.028)	(1.510)	(0.789)
Number of calculations	0.011***	−0.013	0.043
	(0.003)	(0.136)	(0.074)
Time span between calculations (in days)	−0.004***	0.087*	0.014
	(0.001)	(0.052)	(0.023)
Relative change in funding amount	−0.067	−3.306	−0.984
	(0.047)	(2.438)	(1.194)
Backer experience (1 = yes)	0.246***	3.139	−0.136
	(0.028)	(1.940)	(0.837)
Initiator experience (number of campaigns)	0.038	1.641	0.491
	(0.031)	(1.513)	(0.322)
Traffic source (1 = organic/direct visit)	0.225***		
	(0.027)		
σ_{NRV}			7.173***
			(0.414)
σ_{RV}		15.790***	
		(0.514)	
ρ_{NRV}			−0.389***
			(0.120)
ρ_{RV}		−0.252**	
		(0.107)	
Constant		1.387	−8.007*
		(6.996)	(4.213)
Platform fixed effects	Yes	Yes	yes
Time fixed effects	Yes	Yes	yes
Category fixed effects	Yes	Yes	yes
Observations	971	529	442
Log-pseudo-likelihood	−4225.869		
LR test statistic (*p*)		13.141 (0.001)	

Differences in impact of Overplacement (Start) between users and nonusers of reference values on Overplacement (End):

H_0: Overplacement $(\text{Start})_{RV}$ = Overplacement $(\text{Start})_{NRV}$ ==> $\chi^2(1)$ = 44.62, with $p = .000$
H_0: Overplacement $(\text{Start})_{RV} = 1$ ==> $\chi^2(1)$ = 44.89, with $p = 0.000$
H_0: Overplacement $(\text{Start})_{NRV} = 1$ ==> $\chi^2(1)$ = 2.74, with $p = .098$

Notes. The model is estimated by an FIML estimator. Robust standard errors appear in parentheses. The results are robust using a two-step approach.
$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

calculation (coefficient of 0.950, which is significantly different from 1 at p = .098 only). In the lower panel of Table 4, we also test whether the coefficient of *Overplacement (Start)* is significantly different for users and nonusers of reference values; the null hypothesis is no difference between the coefficients. The results show that the impact of overplacement at the beginning of the calculations on overplacement at the end is systematically different at the 1% level ($\chi^2[1] = 44.62$; p = .000) between users and nonusers of reference values. Taken together, these results support Hypothesis 2 and suggest that users of reference values do not ignore the provided information but use the information to exacerbate their estimates.

The coefficients for *Industry experience* and *Education* are positive and significant at the 1% and 5% level, respectively, and for both users and nonusers of references values. These results provide support for Hypothesis 3 that entrepreneurs with higher levels of human capital as drivers of self-efficacy generally adjust their expectations upward. However, the coefficients are also significantly different at the 5% level ($\chi^2[1] = 4.41$; p = 0.036; $\chi^2[1] = 4.31$; p = .038) between users and nonusers of reference values, thus indicating that the tendency to adjust beliefs upward is exacerbated by the use of reference values. Notably, the coefficient for *Relative change in funding amount* is not statistically significant; thus, users do not offset a higher level of overplacement with a lower requested funding goal, which could increase the chances of success.[9]

Control variables in Table 4 are mostly statistically insignificant in the endogenous switching regressions. For instance, age and crowdfunding experience (either as a backer or initiator) of the entrepreneur are not significant. Similarly, the time span between calculation, proxying for preparation, and the number of calculations also are not statistically significant. The only significant variable is crowdfunding reason, which captures whether it has a commercial purpose. In this case, the effect is positive, as expected.

Table 5 provides the results of the counterfactual analysis. The first term is the actual overplacement of users (nonusers), and the second is the hypothetical measure of overplacement that individuals would have obtained had they not used (used) reference values. The difference in means between these two values explicitly quantifies the impact of the use of reference values on overplacement. Furthermore, the results of the t-tests offer support that, in general, our results are not affected by the control variables. In other words, the results of the counterfactual analysis show that some nonusers of reference values would adjust their level of overplacement to the same extent as users of reference values if they use them. This result provides further support not only for Hypothesis 2 on the impact of using reference values but also for Hypothesis 3. The increase in overplacement is driven not by individual characteristics per se but in combination with the use of reference values, thus confirming the cognitive and motivational account of entrepreneurs to protect their self-beliefs.

In addition, we find that the predicted increase attributable to the use of reference values is similar for users and nonusers but that the increase in overplacement is almost four times higher for entrepreneurs in the highest quintile than for entrepreneurs with a lower level of overplacement at the beginning. This evidence is consistent with findings that overplacement is not bad per se but rather depends on the degree to which overplacement is detrimental (Amore et al., 2021; Bernardo & Welch, 2001; Gudmundsson & Lechner, 2013). The finding that entrepreneurs with higher levels of overplacement tend to differentiate themselves even more from the reference value is well in line with our theoretical arguments regarding the motivational processes leading to overplacement.

Table 5. Actual and Hypothetical Overplacement (End) for Users versus Nonusers of Reference Values.

Variable		Actual estimate of users of reference values	Hypothetical estimate of users of reference values if they would have not used reference values	Difference
Quintile of overplacement (Start)	1	3.395	−2.196	−5.591***
	2	16.699	8.189	−8.510***
	3	27.620	15.421	−12.198***
	4	36.858	22.168	−14.691***
	5	58.031	37.793	−20.238***
	Total	28.612	16.353	−12.258***
		Actual estimate of nonusers of reference values	Hypothetical estimate of nonusers of reference values if they would have used reference values	Difference
Quintile of overplacement (Start)	1	0.573	4.613	4.040***
	2	11.655	20.837	9.183***
	3	20.551	33.685	13.134***
	4	27.488	43.474	15.985***
	5	44.177	66.676	22.499***
	Total	19.574	31.950	12.376***
T-tests on overplacement (End)				
$\text{Total}_{\text{RV Hypothetical}}$—$\text{Total}_{\text{NRV Actual}} = 0$				3.221**
$\text{Total}_{\text{NRV Actual}}$—$\text{Total}_{\text{RV Hypothetical}} = 0$				3.338***
($\text{Total}_{\text{RV Hypothetical}}$—$\text{Total}_{\text{NRV Actual}}$)—($\text{Total}_{\text{RV Hypothetical}}$—$\text{Total}_{\text{NRV Actual}}$) = 0				0.117

Notes. Means are reported.
***$p < .01$, **$p < .05$, *$p < .1$.

Post Hoc Analyses on Campaign Start and Campaign Success

While our findings so far establish the failure of calibration to mitigate overplacement, the economic relevance remains unclear. To shed light on this crucial aspect, we run two post hoc analyses with the goal to determine whether overplacement affects the choice of market entry in the form of a crowdfunding campaign and subsequent performance. To do so, we estimate a probit model with the dependent variable equal to 1 if the entrepreneur launches a crowdfunding campaign after using the calculator and 0 otherwise. We find that more overplacing users are more likely to start a crowdfunding campaign, consistent with prior empirical findings (e.g., Camerer & Lovallo, 1999) that these individuals do so because they rely on overinflated estimates of success. This effect is also economically meaningful, as a one-standard-deviation increase in *Overplacement (End)* increases the probability of starting a campaign by 9.2% (= 22.888 × 0.004).

Next, we examine the outcome of the crowdfunding campaigns for the 428 entrepreneurs who decided to launch one. This additional test indicates whether overplacement due to the self-enhancing use of reference values could lead to economic inefficiency. Indeed, overplacement inducing more campaign starts may only be an inefficient outcome if there are significant costs. While we cannot measure the full extent of these costs, one cost we explore here is the higher risk of campaign failure.[10] The dependent variable (*Success of campaign*) equals 1 if the funding goal is achieved and 0 otherwise. To account for the self-selection of starting a campaign, we estimate a two-stage Heckman model with discrete outcome variables (Van de Ven & Van Pragg, 1981), which consists of a selection equation and a discrete outcome equation. In the first stage, we predict the likelihood that an entrepreneur starts a crowdfunding campaign. Then, conditional on selection, in the second stage we estimate the success of the campaign. To obtain consistent estimates in the first-step regression, we use the variable *Time span between calculations (in days)* as an exclusion restriction. This variable measures the time span between the first and last calculation and proxies the degree of preparedness of the campaign. Entrepreneurs who intend to launch a campaign spend more time preparing it and thus are likely to have longer time spans between their first and last use of the calculator. By contrast, we expect little to no effect on performance, in line with prior research (Chwolka & Raith, 2012; Gruber, 2007). The first column in Table 6 corresponds to our first-step estimation, while the last column shows the results of the second-stage estimation. The probit regressions indicate a negative and significant effect of *Overplacement (End)* on campaign success, consistent with the prediction that overplacement reduces success chances. This result is statistically significant at the 1% level. In economic terms, a one-standard-deviation increase in the variable *Overplacement (End)* leads to a 9.2% (= 22.888 × [–0.004]) reduction in the probability of success. Given that the overall probability of success on platforms such as Kickstarter (https://www.kickstarter.com/help/stats) and Indiegogo is in the range of 20% to 40% and relatively stable over time, such a reduction is considerable.[11] Taken together, our post hoc analyses suggest that entrepreneurs suffering from high levels of overplacement, which may be driven by the use of reference values, are more likely to launch crowdfunding campaigns eventually and are also more likely to fail. Both these results indicate that overplacement has meaningful economic consequences for entrepreneurs.

Discussion

The existence, drivers, and consequences of overplacement as a manifestation of overconfidence have been extensively discussed in research in general but received less attention in

Table 6. Determinants of Start and Success of a Crowdfunding Campaign (Marginal Effects).

	Heckman sample selection model	
Variable	First stage: Start of campaign	Second stage: Success of campaign
Overplacement (End)	0.004***	−0.004**
	(0.001)	(0.001)
Number of calculations	0.000	0.003
	(0.003)	(0.004)
Gender (1 = female)	−0.001	0.007
	(0.034)	(0.048)
Education (1 = university degree)	0.039	0.040
	(0.031)	(0.047)
Job status (1 = open for change)	0.042	0.037
	(0.032)	(0.049)
Industry experience (in years)	0.005	−0.006
	(0.004)	(0.007)
Age (in years)	0.000	−0.009*
	(0.003)	(0.005)
Crowdfunding reason (1 = commercial)	−0.032	−0.092**
	(0.031)	(0.046)
Relative change in funding amount	−0.009	0.075
	(0.052)	(0.074)
Backer experience (1 = yes)	0.025	−0.043
	(0.033)	(0.049)
Initiator experience (number of campaigns)	−0.022	−0.068
	(0.024)	(0.048)
Traffic source (1 = organic/direct visit)	0.069**	0.015
	(0.031)	(0.049)
Video (1 = yes)		0.099*
		(0.052)
Funding goal (in USD)		−0.005***
		(0.002)
Time span between calculations (in days)	0.007***	
	(0.001)	
σ		−0.062
		(0.389)
Platform fixed effects	yes	yes
Time fixed effects	yes	yes
Category fixed effects	yes	yes
Observations	971	428
LR test statistic (p)	0.010 (0.912)	

Notes. This table presents the average marginal effects from the Heckprobit sample selection model using maximum likelihood. Robust standard errors appear in parentheses. The results are robust using a two-stage approach.
***$p < .01$, **$p < .05$, *$p < .1$.

the context of entrepreneurship (e.g., Kraft et al., 2022). Moreover, the literature remains largely silent on potential remedies, probably because it is “more newsworthy to show that something is broken than to show how to fix it” (Larrick, 2004, p. 334). Our study provides an answer to recent calls on this gap in general and especially regarding the notion that debiasing attempts may actually exacerbate a bias (Zhang & Cueto, 2017).

In this study, we focus on whether providing information on historical performance data of comparable projects can serve as a potential means to help entrepreneurs calibrate their beliefs. While overplacement is often attributed to imperfect information about others (Moore & Healy, 2008), providing entrepreneurs with better information that allows calibration seems a straightforward solution (e.g., Lovallo & Kahneman, 2003). Nonetheless, there is limited understanding regarding the efficacy of this method in addressing overplacement. In our theoretical discussion, we build on the notion that the effectiveness of any debiasing activity depends on individuals' ability to bypass the cognitive biases leading to the issue itself. There, we develop theoretical arguments to show that the cognitive and motivational accounts leading to overplacement may also affect the use of calibration as a debiasing instrument and, ultimately, exacerbate the issue instead of mitigating it. In line with the theoretical arguments, our findings show that entrepreneurs, especially those with high levels of entrepreneurial self-efficacy, use the information to differentiate themselves even more from the reference group after they see the historical values rather than leveraging the information for honest self-assessment. In turn, overplacement has important economic consequences. We document that overplacing entrepreneurs are more likely to launch a crowdfunding campaign but are also more likely to fail to raise the desired funds. Thus, our study extends current knowledge on the role of overplacement in entrepreneurship.

Theoretical Contributions

Our study sheds light on overplacement and contributes to the scarce literature on debiasing (e.g., Larrick, 2004). While some studies find different debiasing tools to be more (e.g., training and feedback; Lichtenstein & Fischhoff, 1980) or less (e.g., warnings about the risks of the bias; Kaustia & Perttula, 2012) effective in reducing overconfidence, others note that debiasing activities may even exacerbate an issue rather than enabling individuals to bypass the cognitive biases (Sanna et al., 2002; Zhang & Cueto, 2017). We further develop this notion and argue that the effectiveness of debiasing activities depends on the ability to bypass the underlying processes leading to the bias. Our theoretical arguments show that this condition is not fulfilled in the case of calibration with reference values to mitigate overplacement, and thus, this approach backfires.

By investigating the boundary conditions of when and how prospective entrepreneurs make use of contextual information, we extend our understanding of the origins of overplacement and the effectiveness of calibration with reference values as a debiasing device. To the best of our knowledge, we are the first to examine the impact of providing reference values to prospective entrepreneurs as an often proposed solution to mitigate overplacement and find robust results for our hypothesized effects. Our results question the provision of reference values to entrepreneurs as we find that they significantly overinflate their estimates when reference values are provided to them. Grasping the association between overplacement resulting from this provision and entrepreneurial thought patterns and activities lays the groundwork for guiding these processes. Simply providing reference values in the planning stage might not stimulate entrepreneurs to formulate more pragmatic anticipations of new business outcomes and may not rectify overplacement as desired.

However, overconfidence appears in different forms. Overestimation, overprecision, and overplacement are theoretically and empirically different metrics but often demonstrate a negative correlation in real-world circumstances (Cain et al., 2015). While overprecision makes individuals less likely to search for and process relevant information, overestimation induces bias in the search process (Kraft et al., 2022). Our results show that the provision of relevant information about others exacerbates overplacement, but it might be possible to affect overprecision and overestimation positively. For example, an entrepreneur might overplace even more after seeing the reference values but be less confident in the accuracy of this belief. Future studies could examine whether the positive effects on one type of overconfidence outweigh the detrimental effects of providing reference value on another manifestation.

Our work answers recent calls for further research on the “black box” of the pre-entry stage (Bennett & Chatterji, 2023) by providing insights into entrepreneurial planning and decision-making. Our results question the provision of reference values to entrepreneurs as we find that they significantly overinflate their estimates when seeing reference values. Moreover, our study contributes to the debate on entrepreneurial learning by shedding light on how the learning process of entrepreneurs in the pre-entry stage affects decision-making. Recent studies (e.g., Amore et al., 2021) have revealed that cognitive biases among entrepreneurs negatively affect learning from performance feedback. In contrast, our work illuminates the pre-entry process. The inability to revise beliefs is most crucial in the initial stages of entrepreneurial endeavors as it affects the consequent decision to embark on entrepreneurship initially and the subsequent performance (Chen et al., 2018). Therefore, the timing and manner in which potential entrepreneurs utilize reference values is essential for a deeper understanding of entrepreneurial decision-making in the pre-entry phase. This is particularly important in a crowdfunding context; however, while studies have shed light on the structure and outcome of crowdfunding campaigns, little is known about precampaign activities (for a recent review of the literature, see Chen, 2022).

Implications for Practice

Our findings also provide important implications, both for those teaching entrepreneurship and policy makers. Our results question whether reference values should be provided to nascent entrepreneurs to develop more realistic plans, given that many are overplacing and providing reference values may reinforce their cognitive bias. While this conclusion may sound pessimistic, it also provides an avenue for further research and highlights some of the limitations of our study. From a teaching perspective, ensuring that entrepreneurs understand the benefits of historical values as useful estimates might be important when providing reference values. Consistent with the cognitive and motivational account, this is especially crucial for more educated and experienced entrepreneurs. While our study is limited to the examination of the effect of providing reference values, this aspect may require further attention. The way these reference values are presented and explained may affect how overplacing entrepreneurs eventually use them. For example, the extent to which the provision of reference values is put into context when presented to the entrepreneur might help them overcome their myopic focus on their own abilities. Moreover, the way the information is framed and presented to entrepreneurs is an interesting avenue for further research. With more context and an explanation of the benefits of using reference values for calibration, entrepreneurs might recognize the values and use them as intended. While our data include a wide range of different types of entrepreneurs, future research might build on this and examine whether entrepreneurs’ specific motivations to start a venture may yield different reactions.

Our findings might also offer a new justification for bringing external advisers and investors early on board, given that they are more likely—as outsiders—to adopt an outside view and impose the proper adoption of historical reference values. Thus, while the literature typically emphasizes the value-add of external advisers and investors in later stages (e.g., Blaseg & Hornuf, 2023), they may also be beneficial in the planning process. Similarly, having entrepreneurs pitch their ideas to external professional investors or already having investors as shareholders might equally provide feedback to entrepreneurs on their use of reference values. While this is an important implication of our study, the extent to which this should happen in practice remains to be explored.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors disclosed receipt of the following financial support for the research, authorship and/or publication of this article: Daniel Blaseg acknowledges the financial support of the Joachim Herz Stiftung.

ORCID iDs

Daniel Blaseg https://orcid.org/0000-0002-9218-3806
Armin Schwienbacher https://orcid.org/0000-0003-2635-0757

Supplemental Material

Supplemental material for this article is available online.

Notes

1. For example, Hyytinen et al. (2014) report that the majority of entrepreneurs in their sample overplace, with an average estimated failure rate of 15% for their own ventures and 36% for comparable ventures.
2. Aggregated data on new venture outcomes are often readily available. For example, the Kauffman Foundation has published its indicators of entrepreneurship for more than 25 years, including statistics on early-stage survival.
3. To ensure that our findings are not driven by the provision of reference values that the entrepreneurs might perceived as irrelevant or incomparable, we also test the robustness of our results with reference classes that varied in size and the level of comparability. We discuss the respective results subsequently.
4. In the first beta version of the calculator, users were able to see the reference values before providing their own estimates. These data are, however, not included in our analysis. Table B1 in Web Appendix B provides an overview of our sample.
5. As Table B2 in Web Appendix B shows, respondents and nonrespondents do not significantly differ in their use of the calculator.
6. Note that the crowdfunding experience measures here serve as control variables that capture a creator's familiarity with crowdfunding norms and culture. We also have a measure of industry experience in our analysis, which however relates to self-efficacy and thus is used to test H1 and H3. While campaign initiation experience may also seem relevant in terms of entrepreneurial self-efficacy, extant research (e.g., Cornelius & Gokpinar, 2020) consistently shows a negative effect on fundraising performance, which suggests a limited learning effect. As these measures do not belong to the same category, we treat and discuss them separately.
7. Table B4 in Web Appendix B reports details of the matching procedure. As propensity score matching may lead to increased covariate imbalance (e.g., King & Nielsen, 2019), we repeated

this robustness check with coarsened exact matching as an alternative approach (Iacus et al., 2012) and found robust results.

8. Lee and Trost (1978) and Maddala (1983) provide a detailed discussion of the estimation procedure.
9. While we use the first and last round of calculations for the comparison between users and nonusers of reference values, we are aware that other factors might affect our measure of *Overplacement (End)*. Moreover, under the above-average-effect assumption, the entrepreneur might be expected to immediately adjust his or her estimates after the first use of reference values. To check the robustness of our results, we thus compare the changes in overplacement for the group of users of reference values between their first and last round of calculation versus the values from directly before and after using reference values from the same group. The results provided in Table B7 in Web Appendix B, support the idea that the use of reference values is mainly driving the change in overplacement. Moreover, entrepreneurs adjust their estimates immediately after having seen the reference values.
10. On average, users of the calculator estimated spending more than $14,000 on their crowdfunding campaigns up front (e.g., for producing the video and developing a prototype), and 86% of the respondents confirmed in the survey that the costs were equal to or greater than estimated. Another cost would be the failure of the project itself after the crowdfunding campaign ends and the project is undertaken.
11. The historical success probability in our sample is slightly higher, with a value of 38.23%, due to weighting by category and platform choices of the users.

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Author Biographies

Daniel Blaseg is Assistant Professor of Entrepreneurship in the Department of Strategy and General Management at ESADE Business School. He received his Ph.D. from Goethe University Frankfurt and holds master's degrees in law and in finance. He gained practical experience as a consultant for venture capital transactions and as co-founder and CFO of several startups.

Armin Schwienbacher is a Full Professor of Finance at SKEMA Business School, Lille campus. He regularly teaches courses in corporate finance and entrepreneurial finance. He has presented his research on crowdfunding, venture capital, and various other topics in corporate finance at many universities, financial institutions, and international conferences.