

# Absolute, average-based, and rank-based aspirations

Jerker Denrell<sup>1</sup>  | Axel Zeijen<sup>2</sup>  | Manuel Romagnoli<sup>3</sup>  |  
Luigi Marengo<sup>4</sup> 

<sup>1</sup>Warwick Business School, University of Warwick, Coventry, UK

<sup>2</sup>Department of Management, Technology and Economics, ETH Zurich, Zurich, Switzerland

<sup>3</sup>Faculty of Economics and Business Administration, Friedrich Schiller University Jena, Jena, Germany

<sup>4</sup>Department of Business and Management, LUISS University, Rome, Italy

## Correspondence

Luigi Marengo, Department of Business and Management, LUISS University, Rome, Italy.

Email: [lmarengo@luiss.it](mailto:lmarengo@luiss.it)

## Abstract

**Research Summary:** A key strategic challenge is balancing exploration and exploitation. When individuals' exploration activity is guided by problemistic search, should managers encourage high aspirations? Past work has shown that optimal aspiration (the aspiration level that leads to the highest level of performance in the long run) is lower in more turbulent environments. This past work assumes that aspirations are specified as absolute performance, but search is often triggered by performance shortfalls relative to others. Using a simple and analytically tractable model, we show that in such cases, the optimal aspiration may instead increase with turbulence (with rank-based aspirations) or stay constant (with average-based aspirations). Our analyses have interesting implications for target setting and for understanding how aspiration specification impacts exploration in organizations.

**Managerial Summary:** Performance targets (aspirations) drive improvement efforts, and thus it is important to understand optimal target levels. Although

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optimal targets are well known to depend on the uncertainty of the environment, our paper shows that this relationship depends on whether the targets are set in absolute, average-based, or rank-based terms. In more uncertain environments, performance targets specified in absolute terms should be lower, while those specified in rank-based terms (such as aiming to outperform a certain number of competitors) should be higher. The optimal performance target specified relative to average outcomes is always the same: do better than average. We show that these contrasting results are due to the spillover effects of one's own improvements on others. Our paper highlights the implications for how targets should be set in different contexts.

#### KEYWORDS

analytical model, aspiration levels, Problemistic search, social comparison, uncertainty

## 1 | INTRODUCTION

Balancing exploration and exploitation is a fundamental strategic challenge for organizations operating in dynamic environments. Managers must decide how often and when to search for new technologies and products, weighing the costs of exploration against the risk of missing trends that could render their business models obsolete (Bower & Christensen, 1995; March, 1991). An important determinant of the value of search is the degree of environmental turbulence, defined as the frequency and magnitude of environmental change. Previous work has shown that the optimal search level may decrease with turbulence because lengthy searches are not worthwhile when options change frequently in value (Ljungqvist & Sargent, 2012; Posen & Levinthal, 2012; Rustichini & Wolinsky, 1995; Stephens, 1987). If search is triggered when performance falls below aspirations (Simon, 1955), this line of research implies that the aspiration level that induces the optimal amount of search also depends on turbulence. A high aspiration, inducing a prolonged search for a superior alternative, is suitable in a stable environment, while a lower aspiration better suits turbulent environments.

Here, we argue that this conclusion is based on the fact that the decision to search depends on absolute performance levels. However, satisfaction and the decision to search often depend on *relative* performance—how one's outcomes compare to others. For example, Tarakci et al. (2018) show that the willingness of middle managers to search for new strategic initiatives depends more on their performance relative to peers within the firm than on their own historical performance. In this paper, we reexamine the link between turbulence and aspirations when aspirations are defined in terms of relative performance. Our focus is on the aggregate performance consequence of aspirations: what aspiration level maximizes long-term firm performance if all middle managers share it?



Using a simple analytical model, we show that the relationship between the performance-maximizing aspiration level and environmental turbulence depends critically on how aspirations are specified. When aspirations are based on absolute performance, the optimal aspiration level, defined as the aspiration level that maximizes long-term firm performance, decreases with turbulence. In contrast, when aspirations are defined relative to average performance (e.g., to be above-average), the optimal aspiration level remains constant regardless of turbulence. Intriguingly, when aspirations are based on performance rank (e.g., to score in the top 5%), the optimal aspiration level increases with turbulence. By highlighting the importance of average and rank-based aspirations, our study contributes to the literature on exploration and exploitation, performance feedback, and organizational aspirations. It offers practical insights for managers seeking to optimize exploration strategies and set effective performance targets in their organizations.

## 2 | SEARCH AND ENVIRONMENTAL TURBULENCE

Consider a product manager exploring alternative designs to make a product more appealing to its young customers. Should the manager stop after finding an improvement or continue the search for a superior alternative? The optimal strategy depends on the cost of the search (which could involve direct costs or simply the opportunity cost of time) and the possibility of finding superior alternatives. It also depends on how quickly consumers' preferences change. If tastes change rapidly, a prolonged search for a superior alternative is unlikely to pay off because an alternative does not stay superior for long. Instead, it might be better to rush to the market with a less-than-perfect product to take advantage of the opportunity while it lasts (Bingham & Eisenhardt, 2008). More generally, in markets with short product life cycles, managers who spend a long time searching for an ideal design or technology may not take full advantage of fleeting opportunities (Bingham & Eisenhardt, 2008; Choi et al., 2008; Lilien & Yoon, 1990).

To better understand the relationship between turbulence and search duration, researchers from various fields have analyzed stylized models of search in dynamic environments. These models differ in their assumptions about the determinants of search behavior (is it an optimal response to incentives or is it driven by heuristics?) but typically show that the optimal search duration is shorter in turbulent environments. Models of job search in economics, in which job seekers decide whether and when to accept a wage offer (McCall, 1970; Mortensen, 1970), show that the optimal reservation wage is a decreasing function of the probability of being laid off (Ljungqvist & Sargent, 2012). Models of optimal search in economics and ecology have made a similar point (Dall et al., 1999; Ljungqvist & Sargent, 2012; Rustichini & Wolinsky, 1995; Stephens, 1987): optimal search duration is a decreasing function of turbulence (specified as the likelihood of reward changes). More recently, Posen and Levinthal (2012) examined the relation between the optimal level of exploration and the level of turbulence in a multiarm bandit problem with changing payoffs, when exploration follows the heuristic softmax policy. They showed that lower levels of exploration typically lead to higher levels of performance in more turbulent environments.<sup>1</sup>

<sup>1</sup>The exception is in very stable environments: the optimal level of exploration is initially increasing in turbulence but eventually (and predominantly) decreasing. See also Srikanth and Ungureanu (2025) for an extension with different decision processes.

This line of research on optimal search and environmental turbulence has usually assumed, explicitly or implicitly, that exploration decisions are based on absolute reward levels. That is, individuals focus on their absolute level of performance when making decisions about search and exploration. However, satisfaction frequently hinges on relative performance—how one's outcomes compare to others'. Within organizations, individuals may have aspirations based on relative performance or rank, especially when incentives such as promotions or bonuses are given to only a fraction of employees (Becker & Huselid, 1992; Lazear & Rosen, 1981). An extensive literature in psychology and economics shows that, even without explicit incentives, people care about their position in relation to others (Boyce et al., 2010; Genicot & Ray, 2020; Luttmer, 2005; Pardo, 1995). For example, studies have found that income rank affects happiness more than absolute income (Boyce et al., 2010), and employees are concerned about their pay relative to peers (Baumann et al., 2019; Gartenberg & Wulf, 2017).

If individuals care about relative performance, their performance compared to others may influence search behavior. In fact, Tarakci et al. (2018) found that performance relative to peers within the firm was an important determinant of the willingness of middle managers to search. Middle managers were more likely to search for new strategic initiatives when their individual performance was below the average performance of their peers. Hence, performance below the average triggered search in this case.

If search is based on relative performance, the impact of aspirations and their link to environmental turbulence may differ from when it is based on absolute performance. When aspirations are based on absolute performance, they should be lowered in turbulent environments to prevent prolonged searches for fleeting superior options. When aspirations are based on relative performance, the level of performance deemed satisfactory will automatically adjust to changes in turbulence since the performance distribution will change. For example, when turbulence increases, the absolute average performance drops, making it easier to reach the average with a shorter search. Due to such changes in distribution, it is unclear whether and how the optimal aspirations should adjust with increased turbulence.

To study how the optimal aspiration varies with turbulence when aspirations are based on relative performance, we introduce a simple and analytically tractable model of problemistic search. The model focuses on exploration decisions made by individuals within a firm (e.g., middle managers studied by Tarakci et al. (2018)). We assume that individuals explore when their individual performance falls below their aspiration level. Our focus is on the firm-level performance consequences of alternative aspiration levels and aspiration specifications. We take the perspective of a system designer, such as senior management, who wants to maximize the long-term performance of the firm. How should the aspiration level vary with the level of turbulence if the aspirations are based on (a) absolute performance (b) average performance or (c) performance rank? For example, if the aspiration is to be among the  $w$  percent best, how should  $w$  vary with turbulence (the probability that payoffs change) to maximize the aggregate firm-level performance (the sum of all individuals' performances)?

### 3 | MODEL

Our model examines the aggregate performance consequences of different aspiration levels when multiple individuals (within a firm, say) engage in problemistic search in a dynamic environment. Each individual in our model can choose between a large number of alternatives

(representing, for example, different product designs or strategies). Each alternative is associated with a distinct reward. However, rewards can change over time. We assume that individuals engage in problemistic search. That is, search occurs if performance falls below the individual's aspiration level. The individual's aspiration level is defined either (i) as an *absolute* performance level, (ii) relative to the *average* performance, or (iii) in terms of performance *rank*. The purpose of the model is to study how the optimal aspiration level—defined as the aspiration level that maximizes the sum of individual performances—varies with turbulence. That is, if all individuals engage in problemistic search, what level of aspiration would maximize expected long-term performance at the collective level?

More formally, our setup is as follows: There are  $n$  individuals who can choose between  $m$  alternatives in each period  $t=0,1,2,\dots$ <sup>2</sup> The payoff to alternative  $j$  in period  $t$  is  $\theta_{j,t}$ . At the start of the simulation,  $\theta_{j,0}$  is drawn from a uniform distribution between 0 and 1 (we later discuss generalization to other distributions). At the end of each period, the payoff may change. The payoffs to all individuals' chosen alternatives are observed by all other individuals.

Let  $p_{i,t}$  be the performance obtained by individual  $i$  in period  $t$ . In period 0, each individual  $i$  randomly picks an alternative. Individual  $i$  observes (but does not receive) the payoff associated with this alternative. This initial step ensures that the performance gap is defined in period one. In each of the following periods,  $t=1,2,\dots$ , the following events occur (simultaneously) for all individuals:

- Individual  $i$  checks whether  $p_{i,t-1}$ , her performance in period  $t-1$ , is above her aspiration level.
- If  $p_{i,t-1}$  is above the aspiration level, individual  $i$  keeps the same alternative in period  $t$ . Her performance in period  $t$  will remain the same ( $p_{i,t}=p_{i,t-1}$ ) unless the payoff for this alternative has changed ( $\theta_{j,t} \neq \theta_{j,t-1}$ ).
- If  $p_{i,t-1}$  is below the aspiration level, individual  $i$  picks a randomly chosen alternative.
- At the end of each period  $t$ , the payoffs associated with the alternatives may change. With probability  $q \in (0,1)$ , the payoff for alternative  $j$ ,  $\theta_{j,t}$ , changes independently across all alternatives and periods. If the payoff changes, it is drawn again from the uniform distribution.

Our performance metric is expected long-term average performance across all individuals:

$$\pi_T = E \left[ \frac{1}{T} \sum_{t=0}^T \left( \frac{1}{n} \left( \sum_{i=1}^n p_{i,t} \right) \right) \right], \quad (1)$$

where  $T$  is large ( $T \rightarrow \infty$ ). Note that this performance metric can also be interpreted as the long-run expected per-period performance of one randomly chosen individual.

Our model is deliberately simplified to capture and highlight the essential elements. In the extensions section, we relax many of these simplifying assumptions and show that we get similar results.

<sup>2</sup>We assume that the number of alternatives is large ( $m \rightarrow \infty$ ). As a result, there is always an alternative that an individual has not tried so far. This assumption simplifies the exposition, but we show in Online Appendix E that we get similar results if  $m$  is finite.

## 4 | RESULTS

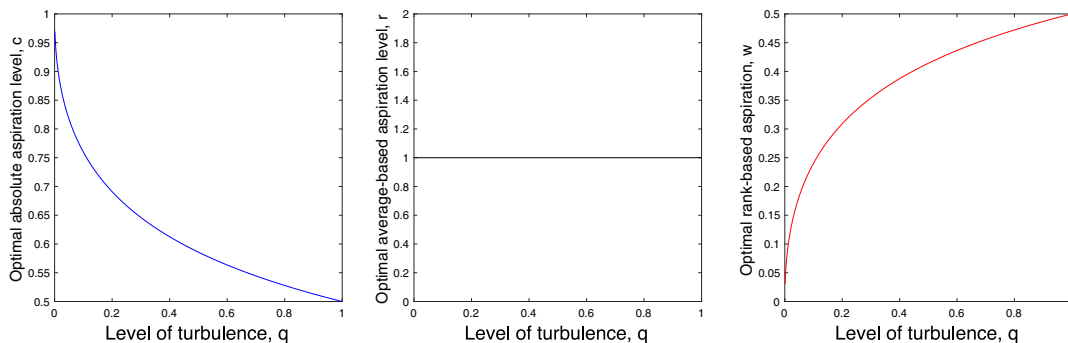
### 4.1 | Absolute aspirations

Suppose first that a performance  $p_{i,t}$  is evaluated as satisfactory if it is greater than or equal to a cutoff value  $c$ :  $p_{i,t} \geq c$ . We assume a fixed aspiration level equal to  $c$  for all individuals and in all periods, and we want to find the value of  $c$  that maximizes  $\pi_T$ . In this analysis, and in the rest of the paper, we focus on the interesting cases where  $0 < q < 1$ .<sup>3</sup>

The value of  $c$  that maximizes  $\pi_T$  depends on the time horizon, the value of  $T$ . However, when  $T$  increases,  $\pi_T$  quickly converges to a fixed value independent of  $T$ . We can solve for the expected performance in this stationary state,  $\pi(c, q)$  (see Online Appendix A).<sup>4</sup> We can then find the value of  $c$  that maximizes  $\pi(c, q)$  (all proofs are in the Online Appendices):

**Proposition 1.** *In the context of absolute aspirations, the value of  $c$  that maximizes the expected performance  $\pi(c, q)$  decreases with  $q$  and is equal to  $c^* = \frac{1}{1+\sqrt{q}}$ , and the expected performance at the optimum is  $\pi(c^*, q) = \frac{1}{1+\sqrt{q}} = c^*$ .*

Proposition 1 shows that the value of the optimal cut-off is equal to the expected performance at the optimal cut-off:  $\pi(c^*, q) = c^*$ . That is, if the optimal absolute cutoff is 0.75, the expected performance of an individual using this cutoff is also equal to 0.75. This occurs because, at the optimum, the system designer is indifferent between the individual keeping  $c^*$  and the individual searching for another alternative with satisfactory performance. Proposition 1 shows that the optimal absolute aspiration level,  $c^*$ , decreases with  $q$  (see Figure 1). Thus, the optimal aspiration level is higher in stable environments and lower in turbulent environments, replicating prior work (Dall et al., 1999; Keller & Rady, 1999; Ljungqvist & Sargent, 2012; Stephens, 1987).



**FIGURE 1** How the optimal absolute aspiration level,  $c^*$ , the optimal average-based aspiration level,  $r^*$ , and the optimal rank-based aspiration level,  $w^*$ , vary with the degree of turbulence,  $q$ .

<sup>3</sup>When  $q = 1$  (payoffs are redrawn in every period) expected performance is independent of the aspiration level and equals 0.5, the expected payoff of a randomly chosen alternative. When  $q = 0$ , individuals should search until they find an alternative with a pay-off (almost) equal to 1 and then stick with it forever.

<sup>4</sup>The expected performance is  $\pi(c, q) = 0.5 \frac{1-c^2(1-q)}{1-c(1-q)}$ . This formula is only rigorously correct as  $T \rightarrow \infty$ , but Online Appendix G shows we get similar results for low  $T$ .

## 4.2 | Average-based aspirations

Suppose now that the aspiration is the average performance of the population. Specifically, in period  $t$  individual  $i$  compares her performance in period  $t-1$ ,  $p_{i,t-1}$ , with the average performance in period  $t-1$ ,  $\bar{p}_{t-1}$ , and considers her performance satisfactory if  $p_{i,t-1} \geq r\bar{p}_{t-1}$ . If  $r=1$ , the aspiration is to be above the mean. If  $r=1.5$ , the aspiration is to be above 1.5 times the mean. When the number of individuals,  $n$ , is large, we can derive the expected performance, for large  $T$ , as a function of  $r$  (see Online Appendix B).<sup>5</sup> We can then solve for the value of  $r$  that maximizes the expected performance for each value of  $q$ :

**Proposition 2.** *In the context of average-based aspirations, the value of  $r$  that maximizes expected performance  $\pi(r, q)$  is independent of  $q$  and is equal to  $r^* = 1$ , and the expected performance at the optimum is  $\pi(r^*, q) = \frac{1}{1+\sqrt{q}}$ .*

If aspirations are specified relative to average performance, the optimal level of ambition (the optimal value of  $r$ ) is the same in both stable and turbulent environments: individuals should always strive to perform better than average (see Figure 1b). Remarkably, the optimal average-based aspiration leads to the same expected performance,  $\pi(r^*, q) = \frac{1}{1+\sqrt{q}}$ , as the optimal absolute aspiration.

## 4.3 | Rank-based aspirations

Suppose finally that individuals have aspirations based on the rank of their performance: individuals want to have a performance that is higher than that of  $w$  percent of all individuals. For example, if  $w=0.6$ , the individual wants a performance higher than 60% of all individuals (and thus to belong to the top 40% of the population). A higher value of  $w$  corresponds to higher aspirations.

To analyze the performance consequences of rank-based aspirations, we again assume that the number of individuals,  $n$ , is large and derive the expected performance as a function of  $w$  for this case (see Online Appendix C).<sup>6</sup> We can then solve for the value of  $w$  that maximizes expected performance for each value of  $q$ :

**Proposition 3.** *In the context of rank-based aspirations, the value of  $w$  that maximizes expected performance  $\pi(w, q)$  increases with  $q$  and is equal to  $w^* = 1 - \frac{1}{1+\sqrt{q}}$ , and the expected performance at the optimum is  $\pi(w^*, q) = \frac{1}{1+\sqrt{q}}$ .*

Proposition 3 shows that, contrary to what was found for absolute aspirations, the optimal rank-based aspiration is an *increasing* function of turbulence. Thus, when ambition is specified in terms of performance rank, the optimal level of ambition is *higher* in *turbulent* environments and *lower* in *stable* environments; a pattern opposite to the case with absolute aspirations. In fact,  $w^*$  is equal to  $1 - c^*$  for any given value of  $q$ . Finally, note that when  $q$  is low, the optimal

<sup>5</sup>As  $T \rightarrow \infty$ , the expected performance is  $\pi(r, q) = \frac{1}{1+\sqrt{1+(1-q)(r-2)r}}$ . Online Appendix G shows that we get similar results for low  $T$ .

<sup>6</sup>The expected performance is  $\pi(w, q) = 0.5 + 0.5(1-q) \frac{w(1-w)}{w+q(1-w)}$ .

ambition is very low ( $w$  close to zero). Thus, in stable environments, it is optimal if all aspire to have a performance just above the worst individual.

Figure 1 presents a graphical summary of the different behaviors of optimal absolute, average-based, and rank-based aspirations as functions of turbulence.

#### 4.4 | No superior aspiration specification

Combining Propositions 1–3, it follows that no aspiration specification is superior to the others:

**Proposition 4.** *The expected performance at the optimal aspiration level is identical for absolute, average-based, and rank-based aspirations and equals  $\frac{1}{1+\sqrt{q}}$ .*

The intuition is that a rank-based aspiration with the appropriate value of  $w$  can implement the optimal absolute cutoff. If the optimal absolute cut-off is 0.75, say, a value of  $w$  can be found (in a large enough group) such that exactly  $w$  percent of all individuals have a performance below 0.75. For this value of  $w$ , a performance equal to 0.75 will be considered satisfactory. The same argument holds for  $r$ . Proposition 12 in Online Appendix F shows that the same result holds for all continuous payoff distributions, not only the uniform.

#### 4.5 | Mechanisms

Different specifications of the aspiration level lead to very different relationships between optimal aspiration and turbulence (the value of  $q$ ): the optimal absolute aspiration ( $c$ ) decreases with  $q$ , the optimal average-based aspiration ( $r$ ) remains the same, while the optimal rank-based aspiration ( $w$ ) increases with  $q$ . What explains these results?

The optimal absolute aspiration decreases with  $q$  because searching for better alternatives is less rewarding when  $q$  is high, since any better alternative is likely to soon be obsolete. This negative association between turbulence and absolute aspiration levels is well known in prior work on optimal search in economics, operations research, and ecology (Dall et al., 1999; Keller & Rady, 1999; Ljungqvist & Sargent, 2012; Stephens, 1987), and in work on the optimal degree of exploration in management (Posen & Levinthal, 2012; Stieglitz et al., 2016). The underlying logic is the same, for example, as in models of optimal search in labor economics, where the reservation wage (the minimum wage a job seeker accepts) is a decreasing function of the layoff probability. “There is less reason to wait for high-paying jobs when a job is expected to last for a shorter period of time.” (Ljungqvist & Sargent, 2012, p. 172).

When aspiration is based on average performance, the optimal aspiration remains  $r^* = 1$  for all  $q$ . Intuitively,  $r^*$  remains unchanged because the level of performance assessed as satisfactory ( $r\bar{p}$ ) will change when  $q$  changes—even if  $r$  stays constant—because  $\bar{p}$  changes. To understand why precisely  $r^* = 1$  is always optimal, recall two facts. First, Proposition 1 shows that the absolute value of the optimal cutoff is equal to the expected performance at the optimal cutoff. Second, if  $r = 1$  the average performance is deemed satisfactory (i.e.,  $r\bar{p} = \bar{p}$ ). For large  $n$ , this average performance equals the expected performance. It follows that the cutoff implied by  $r = 1$  must be the optimal one.

Finally, when individuals have rank-based aspirations, the optimal aspiration,  $w^*$ , is an increasing function of turbulence. To explain this, consider the dynamics generated by

rank-based aspirations, which produce a ratchet effect. Suppose that  $w=0.01$ , and there are 100 individuals; therefore, any performance above the lowest is considered satisfactory. Initially, only the lowest performer (with a performance of 0.01, say) searches until this individual is no longer the worst. When that happens, another individual (say, with a performance of 0.02) will be the worst, and will search, but the level of performance deemed satisfactory (the cutoff) has now “ratcheted up” from 0.01 to 0.02. Even with a low  $w$ , the satisfactory performance cutoff increases over time and eventually reaches a high level. The cutoff would also increase, and more rapidly, if  $w$  was larger. However, a low value of  $w$  has an important advantage: it implies that few individuals search simultaneously ( $w$  percent of all individuals search in any given period). Having many individuals engaged in search simultaneously reduces average performance because the expected payoff from search is no better than a random draw.

If  $q$  is larger, the ratchet effect is less effective. Consider again the case with 100 individuals and suppose that  $q=0.1$ . If  $w=0.01$ , the ratcheting process barely raises aggregate performance above 0.5. The reason is that only one individual searches (the lowest performer). However, on average 10 individuals are subject to a shock in each period ( $100 \times 0.1 = 10$ ), and half of them will draw a performance below 0.5. These five individuals should search, since expected performance during search is 0.5. A higher value of  $w$  allows more individuals to search. The probability of shocks,  $q$ , thus, can be understood as a constraint on how low one can set  $w$ .

## 5 | EXTENSIONS AND ROBUSTNESS

This section considers two extensions, each speaking to the implications of our model. First, does the performance distribution, from which individuals draw, matter? And second, do our results, which formally only hold in the long run and for an infinite number of individuals and alternatives, also hold for shorter periods and few individuals and alternatives? In addition to these extensions, this section introduces several robustness checks of our simplifying assumptions.

### 5.1 | Impact of the performance distribution

In the interest of tractability and ease of exposition, we assumed that the payoffs of the alternatives were drawn from a uniform distribution. However, outcome distributions in real life are rarely uniform; they are often skewed, with high or low outcomes more likely, depending on the context (Chevalier & Goolsbee, 2003; Elberse, 2013; Gaffeo et al., 2008). Outcome distributions can also be fat-tailed, which implies that very high (and low) outcomes are much more likely than under a normal distribution, which can impact search strategies (Azevedo et al., 2020) and incentives (Drugov & Ryvkin, 2020). Managers may have some idea about the shape of outcome distributions they and their organizations are subject to, raising the question of whether our results hold for performance distributions other than the uniform one. The answer is that many of our results hold for any (continuous) performance distribution (see Online Appendix F). Specifically, the result that no aspiration specification is superior (Proposition 4) holds generally. The results that the optimal absolute aspiration,  $c^*$ , is a decreasing function of  $q$  and that  $r^*=1$  hold for any distribution. The optimal rank-based aspiration,  $w^*$  is an increasing function of  $q$  for many other distributions in addition to the uniform, but *not* for some fat-tailed distributions.

Figure 2 shows that the optimal rank-based aspiration increases with  $q$  when performance is drawn from a normal distribution with mean 0 and variance 1, and when performance is drawn from a skewed gamma distribution. The optimal value of  $w$  is a decreasing function of  $q$  if the performance distribution is a Student's  $t$ -distribution with 1.5 degrees of freedom (see the central row of Figure 2). A fat-tailed payoff distribution can change the result because it implies that individuals can discover alternatives with significantly higher payoffs than others. A high value of  $w$  can thus be beneficial (when  $q$  is low) even if it leads to widespread searching. A few high performers can compensate for the low performance of the numerous searchers. However, this reversal of the result only occurs for some fat-tailed distributions. For example, the optimal value of  $w$  is again an increasing function of  $q$  for a Student's  $t$ -distribution with degrees of freedom greater than 2.

Figure 2 also illustrates that the skewness of the distribution impacts the level of the optimal aspiration, but not the association between the optimal aspiration and  $q$ . When it is easier to find good outcomes (positive skew) absolute aspirations should be set higher, and rank-based aspirations can be set lower, because even low-ranking individuals will achieve high performance. Figure 2 does not include the optimal average-based aspiration because it is always the same: do better than the average ( $r^* = 1$ ).

## 5.2 | Do the results change with small numbers?

Our results are derived for large numbers of individuals, alternatives, and time periods (i.e.,  $n \rightarrow \infty$ ,  $m \rightarrow \infty$ , and  $T \rightarrow \infty$ ). Online Appendix G shows that our results hold with fewer individuals; the only difference is that rank-based aspirations become less precise (as there are fewer ranks). Online Appendix E shows that, with fewer alternatives, our model becomes a multi-armed bandit problem, and our results hold.

Online Appendix G shows that our main result—that different aspiration specifications lead to different relationships between optimal aspiration and turbulence—also holds for shorter time horizons. However, the optimal values of the absolute and rank-based aspirations ( $c^*$  and  $w^*$ ) vary with the time horizon. Absolute aspirations should be set lower if time horizons are shorter because there is limited search time. Rank-based aspirations, instead, should be set higher, because the ratchet effect requires time to yield benefits. Both time-horizon effects are stronger when turbulence is low.

## 5.3 | Robustness

Our model is deliberately simplified to capture the essential elements. In Online Appendix G, we explore a number of alternative specifications as robustness checks. We show that our main results regarding the contrast between absolute, relative, and rank-based aspirations hold with different effects of (expected outcomes after) changes due to turbulence; with different specifications of outcome change probability (i.e., not i.i.d.); when individuals can return to previous alternatives (i.e., when they have memory); and when individuals differ in capabilities (i.e., when they draw from different distributions). In Online Appendix H, we show that we get similar, albeit not identical, results when there are search costs.

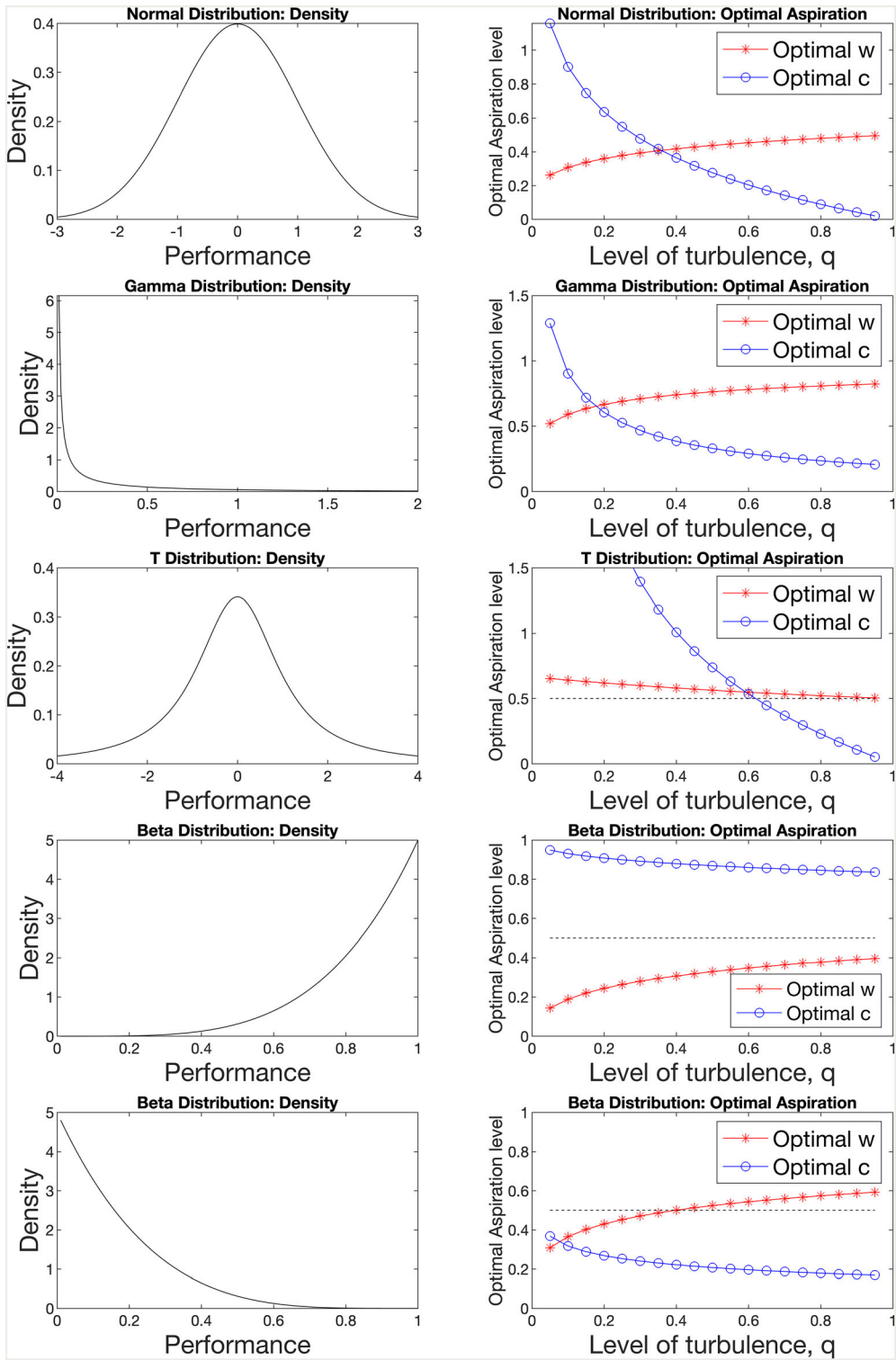


FIGURE 2 Legend on next page.

## 6 | DISCUSSION

Our main contribution is to the large literature on search strategies, spanning management (LiCalzi & Marchiori, 2013; Posen & Levinthal, 2012; Stieglitz et al., 2016), economics (Ljungqvist & Sargent, 2012; Rustichini & Wolinsky, 1995) and ecology (Stephens, 1987). We show that the canonical finding across this literature—that optimal aspiration decreases with turbulence—is in fact contingent on aspiration specification: optimal rank-based aspiration increases with turbulence, while optimal average-based aspiration is constant over turbulence (more specifically, it is always to perform better than average). Secondly, this contingency is further dependent on the task environment. In environments characterized by some “fat-tailed” performance distribution, optimal rank-based aspirations decrease with turbulence.

### 6.1 | Applications and implications

Our model is highly stylized and can be applied to different settings. One intuitive application, which we have followed so far, is that there is a manager who seeks to maximize aggregate organizational performance, and the agents in our model are organizational members contributing to the performance of the organization. One can change this application or interpretation in two ways. First, one can view our modeled agents as individuals within an organization or rather as firms in an industry. Second, one can view our results in a normative way, as informing a system designer maximizing some social optimum. One can instead interpret our results with a descriptive view, as explaining how aspirations of agents (individuals or organizations) result in aggregate outcomes. Each of these applications addresses and complements different literatures, which we discuss in turn.

*Goal-setting within organizations:* Our running interpretation throughout the paper has been of a manager maximizing aggregate organizational performance, which is the sum of the performances of many “problemistically searching” individuals. Under this interpretation, our results directly inform the literature on rewards and incentives in organizations (Becker & Huselid, 1992; Lazear & Rosen, 1981). They may also inform the literature on goal-setting in organizational behavior (Ahmadi et al., 2022; Gary et al., 2017; Locke & Latham, 1990; Sitkin et al., 2011), by explicitly considering how (stretch) goals are specified. Our results also provide direct managerial implications: if managers choose to specify aspirations or targets in a certain way, we show how their *level* should vary with turbulence. For example, if management insists on a rank-based tournament scheme rewarding only a fixed number of individuals, our results show the downside of rewarding only a few individuals in stable environments. Conversely, if managers want to set high aspirations, our results inform how they should be *specified*. For example, in a famous speech, Steve Jobs exhorted Stanford alumni to “stay hungry”; our findings suggest that it matters whether this message was interpreted in absolute or relative terms. Our results about average-based aspirations merit special discussion. Although we showed that

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**FIGURE 2** How the optimal absolute and rank-based aspiration changes with  $q$  for (i) a standard normal distribution; (ii) a gamma distribution; (iii) a Student's  $t$ -distribution with 1.5 degrees of freedom; (iv) a beta distribution with  $\alpha=5, \beta=1$ ; and (v) a beta distribution with  $\alpha=1, \beta=5$ . See Online Appendix F for how the optimal values of  $w$  and  $c$  were computed. Note that optimal average-based aspiration is not displayed; it is always 1, regardless of performance distribution or  $q$ .



no specification of aspirations is inherently superior, average-based aspirations are arguably the easiest to implement: the optimal average-based aspiration is always to do better than the average, regardless of turbulence. Because the optimal level remains constant despite fluctuations in turbulence, management is not required to continuously evaluate the turbulence level.

*Goal-setting between organizations:* A related interpretation of our model is of a population of firms. For example, our discussion can help inform the growing literature on platforms (Rietveld & Schilling, 2021) and platform-based ecosystems (Kretschmer et al., 2022). Platform owners rely on complementors to create value for the platform ecosystem (e.g., app developers provide much of the functionality of smartphones). In this interpretation, our modeled individuals are the platform's complementors, the chosen alternatives are the provided complements, and their payoffs are the performance or appeal of these complements. The platform owner, then, aims to optimize the value of the platform ecosystem. In platform environments there may be turbulence (e.g., in smartphones, when the operating system or its interfaces are updated), which affects the performance of the complements (Kapoor & Agarwal, 2017). Our model can help researchers understand the impact of platform owners' incentive structures. Incentives based on absolute targets (for example, rewards if complementor performance exceeds a threshold) and on rank (e.g., an app store showcasing only the top 10 apps per category) may have very different effects on complementors' search, innovation efforts, and overall value created in the platform ecosystem.

*Individuals as setting aspirations:* One can also interpret our modeled agents as individuals or organizations whose aspirations are not imposed by a system designer. Rather, aspirations may be influenced by norms. In intra-organizational settings, our model can then help understand the implications of such organizational norms. For example, the model shows that higher ambition—specified in terms of rank—leads to superior average outcomes in more turbulent environments, but is wasteful in more stable settings. This could help explain why corporate cultures differ significantly in industries and regions that focus on more or less stable technologies. More generally, our results generate predictions that could be used, for example, in research on organization design.

*Organizations as setting aspirations:* When we interpret the agents in our model as organizations in the absence of an external system designer, our results speak to the behavioral strategy literature on organizational aspirations and problemistic search rooted in the Carnegie Tradition (Audia & Greve, 2021; Cyert & March, 1963; Posen et al., 2018). This literature assumes that the aspiration level is a weighted average of past and peer performance (Bromiley & Harris, 2014; Cyert & March, 1963). Research in this tradition typically focuses on estimating, using field data, the impact of performance cues on behavior (Bromiley & Harris, 2014), with less focus on the performance implications of alternative aspiration specifications. In contrast to our work, the performance feedback literature rarely makes the distinction between average-based and rank-based aspirations. Our results may be helpful to researchers in this tradition who seek to explain variations in innovative performance between firms and industries. For example, if future researchers observe and seek to study multiple highly ambitious organizations in the same environment (i.e., multiple organizations with high aspiration levels), our results suggest that they should also try to observe how these organizations specify their aspirations.

Finally, our results complement a line of work, originating from March (1988), on the performance implications of search driven by adaptive aspirations (Baumann et al., 2019; Dong, 2021; Greve, 2002; Hu et al., 2011; Knudsen, 2008). The main finding is that slower aspiration adjustments improve performance when risk-taking depends on past results

(March, 1988). Moreover, performance improves if aspirations are influenced by social performance rather than adapting to historical performance (Dong, 2021; Hu et al., 2011; Knudsen, 2008). In contrast to this past work, we compare the performance implications of fixed (instead of adaptive) aspirations specified in terms of absolute or relative (average and rank) performance. Because we compare a different set of aspiration specifications, our results are different. For example, the advantage of social aspirations over adaptive aspirations in Knudsen (2008) occurs because adaptive aspirations can cause dissatisfaction even with high-performing options, leading to needless exploration. We demonstrate that a fixed *individual* aspiration based on absolute performance avoids this issue and can achieve performance comparable to social aspirations.<sup>7</sup>

## 6.2 | Limitations

We have developed our model in the simplest possible form, for the sake of transparency and tractability. Of course, this choice comes at the expense of realism. Here, we indicate some directions in which our model could be fruitfully enriched, focusing on the task environment, the aggregation of performance, and individual-level changes.

We treat the search problem as independent draws from a performance distribution. Missing is any notion of developing knowledge, exploring promising leads based on past cues, and lock-in due to path dependency.<sup>8</sup> If individuals realize that they are unlikely to beat others, they may avoid excessive search, altering the results. The shape of the performance distribution can also change over time, and average performance may increase as a result of search, reducing the cost of search.

Another interesting extension would be to look at interdependencies among agents' performance outcomes and how different aspiration specifications impact aggregate outcomes. One of the main characteristics of organizational activities is related to the division of labor, which requires varying degrees of cooperation among individuals. The introduction of aspirations—particularly in relative terms—generates an interesting tension between cooperation and competition, in which some of our current conclusions may not necessarily hold.

Furthermore, our model assumes that aspirations are fixed over time. However, previous work has shown that aspirations are adaptive; they change in response to performance feedback (March, 1988) and environmental conditions (Simon, 1979). Such adaptation processes could be explored as either a mechanism that moderates the impact of turbulence or impacts individual or collective performance.

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<sup>7</sup>Furthermore, models based on March (1988) assume that failing firms are replaced by new entrants (due to “limited liability”), restricting the downside of search.

<sup>8</sup>See for example Zeijen et al. (2025) for an analysis of search with social comparison in a rugged fitness landscape.

## DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

## ORCID

Jerker Denrell  <https://orcid.org/0000-0001-9628-1924>

Axel Zeijen  <https://orcid.org/0000-0002-5506-2140>

Manuel Romagnoli  <https://orcid.org/0009-0005-9951-7118>

Luigi Marengo  <https://orcid.org/0000-0002-8299-7830>

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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