In Search of Behavioral Opportunities from Misattributions of Luck

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ABSTRACT

How performance is perceived and attributed has important implications for strategizing. Much research in the cognitive and social sciences suggests that people tend to mistake luck for skill in evaluations and ignore how future performances regress to the mean. We argue that these systematic mistakes can be translated into an alternative source of profit: informed strategists can take advantage of others' misattributions of luck by exploiting the false expectations and mispricing in strategic factor markets. We also discuss the learning and interdependency barriers that protect, and thus predict the attractiveness of, a behavioral opportunity and suggest approaches to help overcome these behavioral barriers.

Keywords: luck, biases, regression to the mean, strategic factor market, strategic opportunities, behavioral barriers

1. INTRODUCTION

Decades of research in cognitive, organizational, and social sciences shows that people do not always behave rationally (Bazerman & Moore, 2009; Cyert & March, 1963; Kahneman, 2011; Thaler, 2015). Systematic biases in individual actions and organizational behaviors are documented in various contexts, ranging from everyday decisions to high-stakes ones such as political forecasts and mergers and acquisitions (Ariely, 2008; Tetlock, 2005; Zollo, 2009). Less explored is how to overcome these biases to gain competitive advantage and superior performance (see Amit & Schoemaker, 1993; Oliver, 1997; Zajac & Bazerman, 1991, for notable exceptions). In this paper, we argue that these systematic biases in fact illuminate an alternative theory of strategic opportunity based on predictable, false expectations and mispricing in the strategic factor market (Denrell, Fang, & Winter, 2003).

To illustrate our theory, this paper focuses on one ubiquitous bias—misattributions of luck in performance evaluation—and elaborates how the resulting errors can be translated into strategic opportunities. While the role of luck in determining performance differences is widely acknowledged (Alchian, 1950; Arthur, 1989; Barney, 1986; Cohen, March, & Olsen, 1972; Hannan & Freeman, 1984; Merton, 1968; Porter, 1996), recent work has demonstrated theoretically and empirically that higher performances can systematically indicate lower expected skill and future performances (Denrell & Fang, 2010; Denrell, Fang, & Zhao, 2013; Denrell & Liu, 2012; Denrell, Liu, & Le Mens, 2017; Fitza, 2014; Frank, 2016; Mauboussin, 2012). Yet, it is well known that human beings tend to romanticize and attribute successes and failures more to the persons involved than to the situation and predict that these performances are likely to continue (Einhorn & Hogarch, 1978; Kahneman & Tversky, 1973; Meindl, Ehrlich, &

Dukerich, 1985; Ross & Nisbett, 1991). The implication is that the way people mistake luck for skill is predictable and that managers can be rewarded (blamed) for good (bad) luck.

We argue that biases such as misattribution of luck imply systematic false expectations and mispricing in the strategic factor market. A resource in the strategic factor market could be individual employees or business units. For instance, an employee who has been unfairly blamed for failure is an undervalued resource and could be hired by another, more informed employer. In a similar vein, a business unit performing exceptionally well can be an overvalued resource and sold to naïve buyers who ignore regression to the mean. In this sense, biases can create a *behavioral opportunity*—an opportunity that arises because behavioral biases lead to misevaluations.

Not all misevaluations created by biases can generate attractive behavioral opportunities. An opportunity almost anyone can detect and take advantage of is unlikely to provide a competitive advantage. In the same way that attractive industries are those protected by entry barriers, we argue that attractive behavioral opportunities are those protected by *behavioral barriers*—sociocognitive forces (as opposed to economic forces) that protect the biases from being recognized or acted upon. Here we focus on two classes of sociocognitive forces, learning and legitimacy, that act as barriers to thwart attempts to exploit a behavioral opportunity arising from others' misattributions of luck. First, detecting misattributions of luck may be difficult due to the presence of learning barriers—sociocognitive forces that make it difficult to determine whether a prediction is biased. For instance, data may not be readily available to allow managers to detect regression to the mean in performance. Strong learning barriers imply that many managers fail to recognize their prediction biases. This reduces competition for the managers who do recognize regression-to-the-mean effects and thus increases the attractiveness of behavioral opportunities for these managers. Even managers who can learn to recognize regression effects and realize that individuals who failed are not necessarily unskilled may nevertheless refrain from exploiting this opportunity if other stakeholders, such as employees or clients, do not recognize regression effects and do not provide the needed approval and cooperation. An opportunity can thus persist due to an *interdependency barrier*—a barrier to exploiting an opportunity that arises because the stakeholders that a strategist depends on do not understand the opportunity (Suchman, 1995).

More generally, we outline an alternative source of profitability by utilizing the suboptimal sociocognitive processes documented in the behavioral literature to predict when non-economic, behavioral barriers create and sustain competitive advantage. We argue that well-known biases documented in the literature can lead to systematic under- and overestimations in the strategic factor market. We further specify conditions under which these misevaluations are likely to persist: when there are behavioral barriers such as learning and interdependency. Finally, our theory also proposes generic approaches that informed strategists can pursue to create and maintain competitive asymmetry.

The paper proceeds as follows. Section 2 defines what luck is and formally specifies two versions (weak and strong) of regression to the mean and the corresponding misattribution of luck. Section 3 proposes possible strategies to exploit the ignorance of statistical regression effects. Section 4 outlines two behavioral barriers that thwart attempts to exploit a given behavioral opportunity. Section 5 outlines possible generic strategies to overcome the behavioral barriers relative to rivals. We conclude by discussing how our approach complements existing strategy frameworks and provides a template for exploring behavioral opportunities from other well-known biases.

2. TWO VERSIONS OF THE IMPACT OF LUCK ON PREDICTIONS

Observed performances can be attributed to two broadly defined underlying drivers: relatively stable factors and relatively unstable/changeable factors. The idea of luck clearly captures the latter; luck is the impact of a temporary factor that is not expected to persist. When the focus is on individuals, the relatively stable factors include traits such as skill, competency, and motivation. When the focus is on organizations, the stable factors include characteristics such as organizational routines and culture. Keeping this in mind, we will henceforth use the terms skill and luck, following the prior literature on this topic (de Rond & Thietart, 2007; Fama & French, 2010; Frank, 2016; Kahneman, 2011; Liu & de Rond, 2016; Makridakis, Hogarth, & Gaba, 2009; Mauboussin, 2012; Weiner et al., 1971). Whenever performances are not entirely determined by skill but are also impacted on by luck, regression to the mean in performance over time tends to occur (Samuels, 1991; Schmittlein, 1989).

To define regression to the mean in performance over time, suppose performance ($P_{i,t}$) equals skill plus luck: $P_{i,t}=S_i+L_{i,t}$. Here S_i (skill) represents the stable factors of actor *i*, which do not vary with time. (We will relax this assumption in later discussion.) $L_{i,t}$ (luck) represents the changeable factors actor *i* is facing, and these factors do vary over time. In particular, we assume that the value of $L_{i,t}$ is drawn, independently, from some distribution in every period *t*. Let M_i be the expected level of performance of actor *i:* $M_i = E[P_{i,t}]$. Regression to the mean occurs when actors with a *higher* than average past performance ($P_{i,t} > M_i$) have an expected future performance *lower* than their past performance ($E[P_{i,t+1}|P_{i,t} > M_i] < P_{i,t}$). Similarly, actors with a *lower* than average past performance ($P_{i,t} < M_i$) have an expected future performance *higher* than their past performance ($E[P_{i,t+1}|P_{i,t} < M_i] > P_{i,t}$). Thus, performances tend to regress to the mean (i.e., regressing to the individual mean, M_i). The intuition is that an extreme level of performance, high or low, was partly due to good or bad luck (high or low value of $L_{i,t}$). Since luck does not persist, the future performance will be less extreme.

To illustrate regression to the mean, suppose both skill and luck are drawn from normal distributions: $S_i \sim N(0,1)$; $L_{i,t} \sim N(0, v^2)$ where v is the standard deviation of the luck distribution. In this case, the overall mean level of performance across all actors is zero. Figure 1A shows how the average future performance varies with current performances for two different values of v. As a reference point, the gray line in Figure 1A represents the case when luck has no impact at all on performance and performance equals skill: $P_{i,t} = S_i$. If luck plays no role in performance, we should not expect any regression to the mean and past performance is a perfect predictor of future performance (i.e., the 45-degree line in Figure 1A). Whenever luck does play a role, expected future performance is always less extreme than current performance. Moreover, regression to the mean is stronger if luck plays a larger role. Specifically, when v is larger (higher variance in the luck distribution), expected future performance is closer to the overall mean of zero.

Insert Figure 1 about here

While the above illustration assumes that the skill factor stays the same over time, regression to the mean also holds when the skill factor changes over time. For example, suppose actors with high performances are given additional resources, which increase their future expected performance. Specifically, suppose that actor *i*'s future skill ($S_{i,t+1}$) is a weighted average of her current skill ($S_{i,t}$) and current performance ($P_{i,t}$): $S_{i,t+1}=(1-w)S_{i,t}+wP_{i,t}$. Regression to the mean effects hold whenever $w < 1$. When $w = 1$, skill equals past performance, which implies that expected future performance equals past performance: $E[P_{i,t+1}] = S_{i,t+1} = P_{i,t}$. As a result, there is no regression to the mean. Whenever $w < 1$, however, there is regression to the mean.

Alternatively, suppose skill deteriorates over time: $S_{i,t+1}=bS_{i,t}$, where $0 < b < 1$. Regression to the mean continues to hold, as long as the skill factor is relatively more stable (deteriorates less) than the luck factor.

Regression to the mean holds for a wide class of distributions of skill and luck, in addition to the case when skill and luck are both drawn from normal distributions. It does not hold for all distributions, however, and performance may regress to the median or mode rather than to the mean (Schmittlein, 1989). For example, suppose $L_{i,t}{\sim}N(0{,}1)$ but skill is bimodally distributed (e.g., equally likely to be +2 or -2). If past performance is greater than 2, then expected future performance regresses downward. But if past performance is between zero and two, then expected future performance regresses upward, toward the (likely) skill level of +2.

A weaker property, called "reversion toward the mean," does hold for almost all distributions (when past and future performance are identically distributed, for details, see Samuels, 1991). To explain this concept, suppose that u is the average level of performance in some population. Suppose we select *all* actors with a past performance above some cutoff $c > u$. Let $M_{c>u}$ be their average past performance, $M_{c>u} = E\left[P_{i,t}|P_{i,t} > c\right]$. Reversion toward the mean occurs when the future expected performance of these actors, $E\left[P_{i,t+1}|P_{i,t} > c\right]$, is lower than $M_{c>u}$. Similarly, the future expected performance of actors with a past performance below c will be higher than their past average performance: if $c < u$ then $E\left[P_{i,t+1}|P_{i,t} < c\right] > E\left[P_{i,t}|P_{i,t} < c\right]$. Such reversion to the mean does hold for the model in which $L_{i,t}{\sim}N(0{,}1)$ but skill is equally likely to be +2 or -2. The property of reversion toward the mean implies that the expected future mean performance of a selected group is lower (or higher) than this group's current mean performance. This property is more consistent with how managers evaluate and predict performance. (Will the top performers' performances, those above a cutoff, persist or regress to the mean of the population?)

Focusing on all individuals with a past performance above a cutoff, instead of focusing only on individuals with a past performance within a given range, also allows managers to estimate the magnitude of regression to the mean more accurately. Proposition 1 summarizes, in an informal way, the above discussion about the well-known effects of regression to the mean:

Proposition 1 (weak version of luck): When performances are not entirely determined by skill, future performance tends to deviate systematically from past performance. In general, high performances are followed by lower performances and low performances are followed by higher performances, and such regression-to-the-mean is stronger in settings where performance is more unpredictable.

Even if there is regression to the mean, past performance is still useful for predicting future performance. As shown in Figure 1A, higher past performance is still associated with higher expected future performance, that is, $P_{A,t} > P_{B,t}$ implies $E[P_{A,t+1}] > E[P_{B,t+1}]$. The implication is that the higher-performing actors in the past will also likely perform better in the future. We denote this type of regression to the mean *the weak version of luck*.

This monotonicity property does not always hold, however. Consider the following simple model (Denrell and Liu, 2012): skill and luck factors are drawn from normal distributions, $S_i \sim N(0,1)$; $L_{i,t} \sim N(0, \sigma_i^2)$, but the variance of the luck factor is not the same for all actors. Specifically, the standard deviation for actor i is drawn from a gamma distribution: $\sigma_i \sim \Gamma(\alpha, 1/\alpha)$. Thus, the standard deviation differs among actors but remains the same over time for each actor. For instance, actors may differ in their willingness to take risks, resulting in a heavy-tailed distribution of the luck term (a heavy-tailed distribution has a tail that decays slower than the exponential function). Figure 1B shows how the expected future performance varies with the past level of performance for two different values of α. When α is low (equals 0.1), the standard deviation of the gamma distribution is high, meaning that actors may differ greatly in their risk propensities. In such a setting, the association between past performance and future expected performance is non-monotonic at the extremes. In particular, the actors with the *highest* past performance levels have lower expected future performance levels than those with a lower past level of performance. In contrast to the monotonic scenario in Figure 1A, we see rank reversals between the extreme and the less extreme.

Denrell and Liu (2012) discuss the conditions under which such non-monotonic performance associations occur: when the distribution of the luck term is sufficiently more heavy-tailed than the distribution of the skill term.[1] The intuition for non-monotonicity is that actors with exceptional performance are those with a high value of σ_i (e.g., those who take a lot of risks). This also implies that their future performance will regress disproportionally more to the mean than actors with more moderate values of past performance who are likely to have lower values of σ_i.

Proposition 2 (strong version of luck): When the luck term follows a distribution that is more heavy-tailed than the distribution of the skill term, regression to the mean is disproportionally stronger for extreme performances, implying that expected future performance does not increase with past performance. Rather, actors with moderately high (low) levels of past performance can have higher (lower) expected levels of future performance than actors with the highest (lowest) levels of past performance.

We denote this a *strong* version of luck (or strong form of regression to the mean), in contrast to the *weak* version discussed in Proposition 1. As Figure 1B shows, both the weak and the

[1] The inferences we draw from this simple model are not sensitive to the specific distribution choices but are sensitive to the relative heterogeneity between the skill and luck term. That is, performance non-monotonicity occurs whenever the luck term has a heavier tail than the skill term. The more extreme values of performances are increasingly likely to be drawn from the luck rather than the skill term. See Denrell and Liu (2012) for technical details.

strong form may hold simultaneously: First, expected future performance is lower than past performance for actors with a performance above zero (i.e., the weak form of regression to the mean). Second, those with the highest level of current performance have lower expected future performance levels than those with less extreme current performance (i.e., the strong form of regression to the mean).

When does the strong version of luck hold in empirical settings? Theoretically, this depends on when one should expect the luck factor to be more heavy-tailed than the skill factor. When the luck factor is sufficiently heavy-tailed, this means that the difference in skill has almost no impact on extreme performances. Consider the two levels of skill model in which the luck term is drawn from a long-tailed distribution (a subset of heavy-tailed distributions) instead of a standardized normal distribution. It can be shown that $P(S_i = 2|P_{i,t} > c) \cong (S_i = -2|P_{i,t} > c)$ when $c \to \infty$ and that $P(S_i = 2|P_{i,t} < c) \cong (S_i = -2|P_{i,t} < c)$ when $c \to -\infty$ (Denrell et al., 2017). When the current, extreme performance is entirely determined by the luck factor, skill becomes irrelevant and the effects of regression to the mean can be extremely strong, to such an extent that it generates a non-monotonic performance association. This suggests that one should expect the strong form of regression to the mean in settings where the distributions are known to be heavy-tailed, such as wealth (Levy & Levy, 2003), stock market returns (Blattberg & Gonedes, 1974), number of citations (Baum, 2011; Radicchi, Fortunato, & Castellano, 2008), cultural markets (Chung & Cox, 1994; De Vany, 2004; Elberse, 2013; Hamlen Jr, 1991) or firm size (Coad, 2009).

Empirically, the strong version of luck occurs in contexts where extreme performances are unlikely to result from extreme skill but from extreme luck, such as professional sports (e.g., the National Football League and Formula 1 racing), citation at journals' volume/issue levels, movie sales of leading actors/actresses, Billboard musicians, UK firm growth and U.S. public profitability (Liu & Denrell, 2018). These elite sportsmen/teams, movie stars, musicians, leading academic journals, and firms are all highly skilled or efficient but the differences among them can be indistinguishable due to mechanisms such as competitive selection, conformity, or imitation (March & March, 1977). This in turn implies that the extremely high (or low) performances among these highly skilled actors should be attributed more to the circumstances and their future performances are likely to regress disproportionally to the mean. Overall this suggests that one should expect the weak form of regression to the mean in almost all settings while the strong form of regression to the mean should occur in settings where the skill factor is likely to be substantially compressed or where the luck factor is likely heavy-tailed.

3. EXPLOITATION STRATEGIES UNDER REGRESSION TO THE MEAN

Decades of research in cognitive and social sciences show that people make systematic mistakes in attributions and predictions (Jones, 1979; Kahneman & Tversky, 1973; Kelley, 1971; Ross, 1977). In particular, people tend to ignore the effect of regression to the mean and instead predict future performance based on current performance as if the latter is a reliable predictor of the former (Bazerman & Moore, 2009; Harrison & March, 1984; Kahneman, 2011). Support for this idea is not only grounded in experiments on individual decision-making (Kahneman & Tversky, 1973; Ross & Nisbett, 1991), but also comes from research on financial markets (De Bondt & Thaler, 1985) and on how managers and outside observers romanticize high performers (Meindl et al., 1985) and hire stars who eventually do not continue to perform well (Groysberg, 2010). This bias offers a potential opportunity: informed strategists can exploit others' biased predictions if they lead to mispricing of strategic factors (Barney, 1986).

Consider first the weak form of regression to the mean. Suppose most people ignore regression to the mean and naïvely expect that current performance will persist ($\hat{E}\left[P_{i,t+1}\right] = P_{i,t}$) . Such a naïve prediction leads to predictable (1) overestimation when current performance is above the mean and (2) underestimation when current performance is below the mean. That is, the prediction of future performance will be systematically higher or lower than the unbiased expected future performance.

A strategist can exploit such misestimation if it leads to mispricing in the strategic factor market (Barney, 1986; Makadok & Barney, 2001). Consider a particular resource, *R*. The value of this resource to strategist *A* depends on how much *A*'s profits would increase if *A* acquired *R*. Suppose another strategist *B*'s estimate of *R*'s contribution is equal to *R*'s unusually low past contribution, ($\hat{E}[c_{i,t+1}] = c_{i,t}$). Thus, *B*'s estimate ignores regression to the mean and entails a systematic underestimation.

B's biased estimate of *R*'s value can lead to systematic profit opportunities for *A* if *B* is willing to sell the resource *R* for a price equal to (or just above) $c_{i,t}$. Suppose strategist *A* operates a firm that could benefit equally from resource *R*. If strategist *A* takes regression to the mean into account, her estimate of *R*'s contribution may be higher than $c_{i,t}$. Strategist *A* can then buy resource *R* from *B* for a price less than its expected impact on *A*'s profitability. In expectation, strategist *A* makes a profit equal to $\hat{E}[c_{i,t+1}] - c_{i,t} > 0$. Such a systematic profit opportunity exists not because resource *R* is more valuable for *A* than for *B* (cf. Denrell et al., 2003) but because *B* underestimates the value of *R*. For instance, private equity firms target and acquire underperforming firms in industries that have less analyst and media coverage. If other investors underestimate the value of these firms, naïvely expecting past poor performance to persist (Pontikes & Barnett, 2017), sophisticated investors such as private equity firms can exploit this for profit.

How an informed strategist can exploit others' misattribution of luck depends on (1) whether the mistake results in under- or overestimation and (2) whether it is A (i.e., the informed strategist) or *B* (i.e., the naïve strategist) who owns the resource. Table 1 summarizes the exploitation strategies under four possible combinations. Suppose *B* overestimates the value of the resource *R*, predicting its value to be equal to its high recent observed past contribution, $(\hat{E}[c_{i,t+1}] = c_{i,t})$. If *A* owns the resource *R*, *A* can sell the resource to *B*. If *B* is willing to pay a price equal to the observed past contribution of *R* (e.g., the extra sales a location generates), *A* makes an expected profit equal to $c_{i,t} - \hat{E}[c_{i,t+1}]$, which is positive when $c_{i,t}$ is high. A similar tactic can work even when resources are not traded at a market. For example, a salesman with a strong recent performance should apply for promotion or a better package before experiencing the likely regression downward effect.

Insert Table 1 about here

Suppose, in contrast, that the naïve strategist *B* overestimates the value of the resource *R* and also owns it (the bottom left case in Table 1). In general, it is more difficult for a strategist *A*, who understands regression to the mean, to profit from a biased evaluation in this case . *A* cannot benefit by selling the overvalued resource to *B* since *B* already owns it—a well-known limit to exploiting misevaluations in trading (Massey & Thaler, 2013). One alternative is that *A* can sell other resources to *B* that are complementary to *R*. For example, some of the most successful business people during the California Gold Rush and internet boom were not miners or entrepreneurs but those selling tools or consulting services to them. If *B* overestimates the value of a resource *R* (e.g., a gold mine), he would also overestimate the value of other resources he believes are complementary to *R* (e.g., pickaxes and jeans). Take another example. If *B* believes a central location is very valuable because it exposes tourists to his shop, then *B* might also overestimate the value of storefront designs. Strategist *A* could profit by selling such complementary resources to strategist *B*. Another way *A* could profit is by focusing on market niches that strategist such as *B* will ignore because they overestimate certain resources. For example, if the value of central locations is believed to be high, and most firms focus on such locations, *A* could benefit by focusing on peripheral locations where the competition is likely lower.

Similar considerations apply to the case in which *B* underestimates the value of the resource *R*. If B owns the resource, A could benefit by acquiring the undervalued resource *R* and its complementary resources from *B*. If *A* owns the resource *R*, it is not obvious how a strategist *A* could profit from *B*'s underestimation in this case. *A* can try to acquire from *B* the resources that are complementary to *R*, if *B* also underestimates the value of those resources. *A* can also focus on areas neglected by firms that undervalue resources *R*, such as in domains that recently experienced salient failures (Pontikes & Barnett, 2017). Propositions 3A-D in Table 1 summarize the above discussions.

The strategies discussed so far apply to both the weak and the strong versions of luck. With the expected rank reversals under the strong version, however, an additional trading strategy is possible. To explain this trading strategy, suppose the contribution of resource i is observed to be higher than the contribution of resource j: $c_{i,t} > c_{j,t}$. Under the strong form of regression to the mean, it is possible that a resource with an observed lower contribution is worth more; that is, it is possible that $E\left[c_{j,t+1}|c_{j,t}\right] > E\left[c_{i,t+1}|c_{i,t}\right]$. As Figure 1B shows, this occurs for very high or very low observed contributions. Suppose that strategist *B* does not take such strong form of regression effects into account but estimates the value of resources i and j to be equal to their observed contributions ($\hat{E}[c_{i,t+1}] = c_{i,t}$). This implies that strategist *B* would value resource i more than j since the observed contribution of i is larger than the observed contribution of j ($c_{i,t} > c_{j,t}$). If strategist *A* owns resource i and strategist *B* owns j, strategist *A* can exploit the misestimation on the part of *B* by proposing a trade: strategist *B* gets resource i and strategist *A* gets resource j.

The possibility of a trading strategy implies that strategist *A* can benefit from misestimation even if there is no market for resources in which prices reflect estimated contributions. Suppose, for example, that all employees in a given occupation earn the same wage. Consider a particular employee who happens to be especially unproductive during one year. If most employers fail to take regression to the mean into account, they will underestimate the value of such an employee. How could a strategist *A* exploit such misestimation? If the wage could be changed to reflect estimated productivity, strategist *A* could offer the employee a higher wage than he currently gets and still benefit. If the wage is fixed, however, this strategy is not possible. Under the strong form of regression to the mean, however, the strategist *A* could potentially offer a trade. Suppose there are two employees and the observed productivity of employee *i* is higher than the observed productivity of employee *j*. Under the strong form of regression to the mean, employee *j* could still have a higher expected productivity. If strategist *B* currently employs *j* and strategist A employs *i*, strategist *A* could suggest a trade.

Proposition 4 (exploitation strategies under the strong version of luck): When the impact of luck is strong enough to generate rank reversals, the informed strategist A can profit by exchanging the resources that had extremely high (or moderately low) past contributions for the naïve strategist B's resources that had moderately high (or extremely low) past contributions.

The above discussion assumes that managers are either sophisticated or naïve, but in reality most managers are somewhere in between. Indeed, experiments show that most decision-makers discount observed performances to some extent when making predictions: predictions about the future are usually a weighted average of the observed performance and a prior but the weight on the observed level of performance is too high compared with a normative benchmark (De Bondt & Thaler, 1985; Denrell & Fang, 2010; Huberts & Fuller, 1995; Massey & Thaler, 2013). This suggests that the basic idea holds: behavioral opportunities exist if not all managers are fully sophisticated.

It is also important to point out that the strategies outlined above are inherently risky. Performances above and below the average will, on average, regress to the mean but it is not guaranteed that a specific portfolio based on these strategies will have a positive return. Moreover, it is possible that a strategist can only benefit from misestimation once the bias disappears. Suppose strategist *A* acquires a central location that is underestimated by most and that *A* cannot profit from this by opening a shop but only by reselling this location later. In this case, *A* can only profit when others realize their mistake or positively update their evaluation for other reasons. However, as Keynes put it, “[t]he market can stay irrational longer than you and I can remain solvent” (see, Shilling, 1993, p.236). Strategists should search for contexts in which the expected profit of exploiting others’ misevaluation is the highest to offset the risk, which is the focus of the next section.

4. BEHAVIORAL BARRIERS PROTECT THE OPPORTUNITIES FROM BEING EXPLOITED

An individual bias, such as a failure to understand regression to the mean, does not necessarily result in market level biases. More generally, not all individual- or firm-level biases result in attractive behavioral opportunities. A mistake almost anyone can detect and take advantage of is unlikely to remain an attractive opportunity or provide a competitive advantage. In the same way that attractive industries are those protected by entry barriers and attractive resources are those protected by imitation barriers, attractive opportunities based on biases are protected by behavioral barriers. We outline two classes of sociocognitive forces, learning and legitimacy, that act as barriers to thwart attempts to exploit a given behavioral opportunity.

Behavioral Barriers Can Reduce the Number of Rivals that Try to Exploit Misattribution of Luck

The strategies discussed in the last section assume there is no competition—no one except the focal strategist can recognize and exploit failure to understand regression to the mean. If there was such competition, the profit opportunities would be reduced or eliminated. Whether a behavioral opportunity is attractive or not depends on how many (and how well) rivals understand regression to the mean and whether they also try to exploit the same behavioral opportunity.

Insert Figure 2 about here

Figure 2 illustrates how the profits from exploiting the misattribution of luck depend on competition. Figure 2A focuses on the scenario in which a strategic resource is undervalued due to recent poor performance. Suppose most firms do not understand regression to the mean. The common prediction then fails to take regression to the mean into account and will underestimate the value of the resource (and its complementary resources). The sophisticated unbiased prediction takes regression to the mean into account. The difference between the biased common prediction and the unbiased one is the potential profit a sophisticated strategist *A* could earn (on average) by acquiring the resource. If rival strategists also understand regression to the mean, they will also bid for the resource. The realized profit is the difference between the highest bid from a rival strategist, which is the price the strategist *A* has to pay to acquire the resource, and the unbiased prediction. It is possible that all profits will be eliminated in the presence of a single competing bidder (Bertrand competition). In general, one would expect that a larger number of competing bidders will reduce the realized profit by increasing the price a strategist *A* has to pay for the resource. Figure 2B illustrates the effect of competition when a strategist *A* owns a resource (or its complementary resources) that is overvalued by others. Again, the presence of rivals who also own the resource and wish to sell it to naïve actors who overestimate its value will reduce profits (e.g., copycat tool shops during the Gold Rush). In this scenario, the presence of competing sellers implies that the strategist *A* will have to sell the resource for a lower price than otherwise, reducing her profits.

The fact that the profit from exploiting misattribution of luck is larger when few other firms understand and try to exploit regression to the mean implies that strategists should search for contexts in which barriers prevent the entry of competing firms. The basic argument is similar to the idea that attractive industries are protected by entry barriers (Porter, 1980) and that strategic resources are those that are protected by isolating mechanisms that deter comprehension and imitation (Barney, 1991; Rumelt, 1984). Such barriers make it more difficult for firms in general to take advantage of an opportunity, making the opportunity more valuable and more likely to exist for firms that can overcome the barriers. While much of the strategy literature has focused on economic barriers that prevent imitation and entry (such as patents and economies of scale), opportunities can also be protected by behavioral barriers, including difficulties of learning and problems of coordination and legitimation (Oliver, 1997).

Proposition 5 (general behavioral barrier): Exploiting misattribution of luck has a greater expected return when behavioral barriers make it less likely that rivals recognize, understand, or pursue the same opportunity.

We argue that behavioral theories can help predict when there is less competition and hence more attractive behavioral opportunities. We discuss two classes of behavioral barriers: learning barriers and interdependency barriers, drawing from two prominent, behaviorally grounded literatures (organizational learning and institutional theory, respectively). There are many other constraints in learning and social interactions that can create strong behavioral barriers. Here we focus on the ones most relevant to the focal bias of misattribution of luck.

The Learning Barrier: Difficulties in Detecting Regression to the Mean

The difficulties of learning moderate the extent to which evaluators could understand regression to the mean and, in turn, predict the attractiveness of a behavioral opportunity. Learning processes involve updates of beliefs (staying the same, reinforced, or revised), and the sources that trigger the updates can be direct experience, the experience of others, or how these direct and indirect experiences are interpreted through evaluators' conceptual frameworks or paradigms (Levitt & March, 1988). We will first elaborate on the cognitive aspect of learning barriers before discussing how other social cognition can make learning even more challenging.

A strategist is unlikely to profit much from a misevaluation of luck if competitors can easily learn from experience to make accurate predictions. Suppose rivals initially underestimate the value of a resource but it is easy for them to learn from experience to revise and accurately value the resource. It follows that any profit opportunity will be eliminated if learning from experience is easy. In contrast, if learning from experience is difficult (or even superstitious), in the sense that rivals are unlikely to learn to accurately value the resource, mistaken predictions can persist for a long time, and the rewards from exploiting misattribution of luck are likely larger because the differences between rivals' predictions and the unbiased prediction persist longer.

This argument implies that a strategic opportunity is likely to be more attractive, in the sense that the bias is larger and/or it will last longer, in settings where learning is difficult. When is learning more difficult? This is partly determined by whether the learning environments are "kind" or "wicked"—a distinction developed in the literature of judgment and decision-making (Hogarth, 2001). A kind learning environment involves the necessary conditions for accurate inferences (such as uncensored data, speedy/reliable feedback, stable task environment) while a wicked learning environment invites flawed inferences (such as polluted data, sporadic/unreliable feedback, fleeting task environments). We also draw on the literature on organizational learning (Cyert & March, 1963; Denrell & March, 2001; Levinthal & March, 1993), which has identified a number of settings, including noise, interdependencies, and competence traps, in which learning from experience is unlikely to quickly identify the business practice with a higher level of payoff.

To illustrate our argument, consider first a kind learning environment (Hogarth, 2001). The task is to learn to predict an actors' expected performance in Period Two given his observed performance in Period One; that is, the task is to learn the function $E[P_{i,2}|\ P_{i,1}]$. Suppose the underlying data generating model is $P_{i,t}=S_i+L_{i,t}$, where S_i is the skill of actor i and $L_{i,t}$ is an error term that is independently drawn in every period. We assume that actor i performs the same task repeatedly (stable task environment), that his skill remains the same (S_i remains the same), and that data on many periods is immediately available (uncensored data with speedy/reliable feedback). In such a setting, learning is relatively easy since the learning environment enables reliable estimations: an evaluator can identify $E[P_{i,2}|\ P_{i,1}]$ by computing how average performance in Period Two varies from performance in Period One. An evaluator who initially does not take regression to the mean into account (i.e., her initial prediction is $\hat{E}\left[P_{i,2}\right] = P_{i,1}$) will eventually learn from experience and make predictions that take regression to the mean into account. If all evaluators quickly learn to make accurate predictions, any profit from this underestimation will quickly disappear as rivals learn to accurately estimate the value of the resource.

In many settings the learning environment is less kind. For example, little data may be available. As a result, an evaluator who does not take regression to the mean into account will not have sufficient evidence available to conclude that her predictions were inaccurate. Such an evaluator may continue to underestimate an actor with poor past performance for a substantial period, until sufficient data become available. Lack of data is especially problematic for the strong form of regression to the mean. The non-monotonic association occurs at extreme levels of performance and cannot be reliably estimated unless a lot of data is available. Consider, for example, failures in complex systems, such as nuclear reactors (Perrow, 1984; Rudolph & Repenning, 2002). A skilled operator may be able to repair a failure if it occurs in an isolated part of the system. If a failure occurs in an interconnected system, additional errors are triggered before a skilled operator can fix existing ones. This suggests that catastrophic failures, which occur when a chain of failures is set in motion, may be less indicative of poor operator skills. Rather, they can be more indicative of the fact that failure occurred in a fragile part of the system (Perrow, 1984). It is thus possible that operators associated with minor errors, which perhaps could have been preventable, are less skilled (on average) than operators associated with catastrophic errors, which seldom can be prevented (Dorner, 1996). However, since catastrophic failure is a rare event, it is difficult to test this theory and reliably estimate the skills of operators associated with catastrophic failures.

Data may also be subject to selection bias. For instance, second-period performances may not be available for actors with poor first-period performance as they are less likely to participate again. For example, employees with poor initial performance, who are believed to be unskilled, may be dismissed or assigned to tasks in which performance does not depend much on their skills. If no data on second-period performances is available for actors with poor initial performance, an evaluator may continue to underestimate such actors (i.e., believing that their skill is identical to their poor initial level of performance $\hat{E}[S_i] = P_{i,1}$). Because data are available on second-period performances of actors with high first-period performances, the evaluator will be able to observe that their performances regress to the mean (i.e., observing that $E[P_{i,2}] < P_{i,1}$). Such a reduction in performance, however, may be blamed on laziness or complacency (Kahneman, 2011).

It is important to note that the availability of data does not change whether regression to the mean occurs but impacts on whether a strategist can detect regression to the mean and accurately estimate its magnitude. It is easier to detect regression to the mean if a lot of comparable data is available. As a result, behavioral opportunities are less likely to persist in large data settings. Limited data (such as mergers and acquisitions performances in niche industries) increase the chances that regression to the mean remains undetected but also makes it more risky to exploit such an opportunity because a strategist does not know the magnitude of regression to the mean or if it even exists. If sales have been exceptionally high, a strategist may expect regression to the mean but cannot precisely estimate the net present value of a firm without comparable data. Thus, data availability impacts on both the persistence of behavioral opportunities and the risks of exploiting them. We return to this point in the next section on overcoming behavioral barriers.

Regression to the mean can also be difficult to detect if skills improve over time. Competence usually improves more rapidly initially and then slows down (Argote & Epple, 1990). The initial improvement in competence can offset the statistical regression effect, making the performance appear to be non-regressive. When actors' competence reaches a plateau, performances will start to be regressive again. Understanding and estimating the magnitude of regression effects is challenging in such a setting because observed performance changes can result from both changes in skills and regression to the mean.

Forecasts can also be subject to a self-fulfilling prophecy, which can make it difficult to detect regression to the mean (Einhorn & Hogarch, 1978). To illustrate this possibility, suppose $P_{i,1}=S_i+L_{i,1}$, where S_i and $L_{i,1}$ are both independently drawn from a normal distribution with mean zero and variance one. For this model, it is known that $E\left[S_i|\ P_{i,1}\right] = 0.5P_{i,1}$ (DeGroot, 1970). Suppose now that actors who do well in the first period ($P_{i,1}$ is high) are given additional opportunities and resources that enable them to perform even better in the second period. For example, entrepreneurs who succeed are likely to come into contact with investors who can help them in subsequent ventures. To reflect this, suppose the second-period performance of actor i is $P_{i,2}=bP_{i,1}+S_i+L_{i,2}$. Here b measures how much first-period performance enhances second-period performance and $L_{i,2}$ is an error term drawn from a normal distribution with mean zero and variance one. Because expected second-period performance depends on skill as well as on performance in the first period, we get $E\left[P_{i,2}|\ P_{i,1}\right] = (b+0.5)P_{i,1}$. Consider the case in which b equals 0.5. In this case, $E\left[P_{i,2}|\ P_{i,1}\right] = P_{i,1}$. Thus, when b equals 0.5, a naïve evaluator, who falsely believes that past performance is a good estimate of skill ($\hat{E}[S_i] = P_{i,1}$) and falsely believes that past performance predicts future performance, will make accurate predictions on average (his estimate will be $\hat{E}[P_{i,2}] = P_{i,1}$). Because his predictions about performance are unbiased, the naïve evaluator may not discover that his predictions of skill are too extreme. That is, his reaction to observed performance creates a learning barrier that reduces the chance of discovering the flawed theory he applies in prediction. A sophisticated strategist could take advantage of such a misperception of skill by bidding for actors with unusually poor initial performance and giving them a second chance.

Finally, learning can also be moderated by various interactive, sociocognitive forces. For example, regression to the mean may appear to be weak when it interacts with other social biases such as stereotyping (Fiske & Taylor, 2013). Employees who fit a favorable stereotype are more likely to be hired and given additional resources. Their successes can reinforce the stereotype. For instance, systematic changes in performances may appear to be applicable only to counter-stereotypical employees, but these changes are likely attributed to their negative stereotypes (such as laziness) instead of regression to the mean. Since the explanations may fit with the managers' conceptual frameworks, paradigms, or even prejudices, organizations may evaluate this performance feedback less critically, increasing the chance of failing to recognize the mistakes (Jordan & Audia, 2012). Effective learning is difficult when sociocognitive forces tend to reinforce, instead of correct for, flawed beliefs. Our theory, then, predicts that these learning barriers can create attractive behavioral opportunities.

More generally, the idea that difficulties of learning can sustain competitive advantage is not new. For example, causal ambiguity in competency-based advantage can raise barriers to imitation (Reed & DeFillippi, 1990) and sustainable advantage of a firm can occur when rivals continue employing suboptimal strategies that are self-confirming (Ryall, 2003, 2009). Here we focus on the challenges of learning about regression to the mean and how they help the search of an alternative source of strategic opportunity.

Proposition 6 (learning barrier): A behavioral opportunity from misattribution of luck persists longer and has a greater expected return when detecting regression to the mean is more difficult due to lack of data or other confounding changes in performance that offset the statistical regression effect.

The Interdependency Barrier: Difficulties in Convincing Others about Regression to the Mean

A strategist who wishes to take advantage of a strategic opportunity can often only do so by convincing and cooperating with others, such as employees and shareholders. The strategist must convince stakeholders that an opportunity exists that is worth investing time and money in. Yet, explaining and motivating stakeholders to adopt a strategy is more difficult when the strategy is unique (Benner & Zenger, 2016; Litov, Moreton, & Zenger, 2012). Here we argue that explaining and motivating people in favor of a unique strategy is especially problematic for a strategist who wishes to take advantage of a behavioral opportunity. A behavioral opportunity exists because many people are biased and hence under- (or over-) estimate the value of a resource. The irony is that the bias that underpins an opportunity also makes it difficult to take advantage of. That is, if most stakeholders, including shareholders and employees, suffer from the same bias, the strategist may have a difficult time explaining and convincing these stakeholders that an opportunity exists because it violates “cognitive legitimacy” (Suchman, 1995).

Consider the case of an employee who initially performed very poorly at a task. The common-sense prediction is that this employee is poorly skilled and will continue to perform equally poorly. Suppose that most employers make this common-sense prediction and underestimate the performance of this employee. A sophisticated strategist may offer the employee a salary that is slightly higher than what this employee is offered by most other employers. Suppose, however, that the strategist has to motivate the board or other employees in favor of this hiring decision. If the members of the board or the employees do not take regression to the mean into account, they may fail to comprehend this strategy and object to hiring an individual with poor past performance. They may attribute this hiring decision to favoritism (the strategist has some personal reasons for hiring this employee) or simply poor judgment.

Even if members of the board or employees personally understand regression to the mean, they may argue that it would be difficult to explain and motivate the decision to hire a poor performer to many relevant others, including customers. For example, if the firm is involved in consulting, customers may care about the track record of the employees because customers use the track record of the consultants to infer their competence. If customers do not understand regression to the mean, or simply do not have the time or data available to examine if the naïve prediction works well or not, customers may rely on the simple heuristic that future performance usually equates to past performance. As a result, customers may resist working with consultants with poor past performance. Knowing this, employers may resist hiring individuals with a poor track record, even if they personally suspect that the performance of these poor performers will regress to the mean. More generally, whenever outcomes depend on the reactions of others, people may refrain from acting upon a correct inference when they are uncertain whether others have come to the same conclusion. Instead, they may compromise and use conventional ways of evaluating actors; for example, relying on past performances to predict future performance even if they privately know that such a prediction is an unreliable or biased estimate of actors' quality (Correll, Ridgeway, Zuckerman, & Jank, 2017).

The fact that strategists may avoid exploiting a biased evaluation out of fear that others will misunderstand such a strategic move or interpret it as a sign of incompetence implies that the opportunity is more likely to persist if such an interdependency barrier exists. If there is no barrier of this type (i.e., when all actors who understand the opportunity can exploit it) and there is no need to convince and work together with others, the opportunity is likely to vanish quickly. If few actors can exploit it, in contrast, the opportunity is likely to persist longer. The opportunity is also more likely to be attractive, for those who can take advantage of it, because there is less competition.

Proposition 7 (interdependency barrier): A behavioral opportunity from misattribution of luck persists longer and has a greater expected return when exploiting the opportunity requires convincing and cooperating with many stakeholders.

More generally, behavioral opportunities are contrarian in nature and doing things differently is usually associated with others' misunderstanding, disapproval, and backlash (Gavetti, 2012; Oliver, 1997). We focus on how cognitive legitimacy may inhibit evaluators from engaging in unusual actions. Many other social dynamics, such as conformity or institutional forces, can also deter evaluators from expressing what they personally believe (Benner & Zenger, 2016; Correll et al., 2017; Oliver, 1991, 1997; Suchman, 1995). A common feature of these dynamics is that the social cost may overwhelm the economic benefit of exploiting a behavioral opportunity. This is bad news for market efficiencies (e.g., resources may be systematically mispriced due to factors unrelated to merit). But this is good news to strategists who are ready to exploit others' mistakes—the stronger these behavioral barriers are, the more attractive these behavioral opportunities are for the strategists who are able to overcome these barriers.

5. OVERCOMING BEHAVIORAL BARRIERS

We outlined an alternative source of profit in the previous section: attractive opportunities from misattribution of luck exists when there are strong behavioral barriers protecting the opportunities. Behavioral theories can be normatively useful because they not only illuminate an alternative source of profit (e.g., mispricing due to a common bias such as ignorance of regression to the mean) but also predict when the bias creates a more attractive opportunity (e.g., fewer rivals can recognize or act upon the opportunity due to learning or interdependency barriers). However, the behavioral barriers collectively pose a paradox: attractive opportunities from others' misattribution of luck are most likely to exist in contexts where they are also most challenging to detect, learn, and act upon. Why is it that some strategists can succeed in exploiting strategic opportunities while others fail? A theory of competitive advantage would not be complete if it did not address how competitive asymmetry is created, sustained, and defended. We argue that behavioral theories can also help illuminate how a strategist could exploit these opportunities more effectively than the rest.

How to Become Less Dependent on Others

To exploit a behavioral opportunity, a strategist should first examine whether she can be in a position to overcome the interdependency barrier. Behavioral opportunities protected by interdependency barriers will be especially valuable for strategists who can ignore social constraints and who are less dependent on convincing and gaining the approval of others. If a strategist needs others' resources (e.g., financial or social support) to implement her strategy, the strategist is then constrained by whether these stakeholders endorse the strategy (Barney, 2018;

Pfeffer & Salancik, 1978). Stakeholders may withdraw their support if the strategy is based on regression to the mean but the stakeholders fail to comprehend it. For example, a strategist in a private firm does not have to convince shareholders about the benefits of a strategy and may thus be able to take advantage of opportunities unavailable to others (Benner & Zenger, 2016; Shleifer & Vishny, 1997). Similarly, a company that sells advice to customers has to explain why their advice would lead to improved efficiency to customers. Contrast this with a company that is involved in production: this company can implement the advice and produce a product with increased efficiency without having to explain to outsiders why this procedure would work.

More generally, there is a continuum of the level of dependency, and the financial market represents the lower end. For example, opportunities in stock markets are often created by noise traders' suboptimal investment strategies (Delong, Shleifer, Summers, & Waldmann, 1990). Traders can pursue these opportunities swiftly whenever they are identified. However, traders are not entirely free unless they invest with their own money. Otherwise, traders can lose capital support from their funders if the formers' trading strategies are too sophisticated to understand for the latter (Shleifer & Vishny, 1997). This interdependency constraint is greater for strategists outside of the financial markets—they can lose both capital, resources, and social support if their stakeholders fail to comprehend their strategy, misinterpret the exploitation tactics, or discount the outcome for its uniqueness.

We suggest that strategists should focus their search for opportunities in settings where they are less dependent on others than their competitors are, if such settings exist. For example, a firm with low status and few applicants for new positions may not have to justify why they hire someone with poor past performance. Strategists may also need to reduce dependency on others before pursuing a behavioral opportunity. One way to reduce dependency is to ensure that outcomes are objectively evaluable. For example, a strategist who acquires an undervalued resource is less likely to benefit from the resource if its future contribution is difficult to evaluate. The ambiguity may lead the stakeholders to anchor to their previous underestimation. This suggests that strategists should evaluate whether the misevaluated resources, once acquired, can generate value in an unambiguous manner. For example, private equities' due diligence usually takes into account whether the acquired firms' performances can be improved along metrics that potential future buyers could understand, such as by obtaining higher market share or return on assets/investment. This enhances the chance of successful exit and positive return.

Next, a strategist should search for behavioral opportunities outside her immediate network. The interdependency barrier is stronger in interconnected cliques. This poses a dilemma: a learning barrier may be easier to overcome within networks because information is more readily available to those already in the networks than it is to outsiders who might want to profit from it. But the interdependency barrier predicts that this is also an occasion when unusual actions may attract stronger resistance. Potential returns to carrying out unusual actions can be outweighed by the penalty associated with deviating from local norms. This implies that strategists should reduce dependency by looking for misestimation in remote, less constrained parts of their networks.

Third, strategists could also proactively de-couple themselves by distancing from stakeholders who are bounded by norms. Consider Michael Burry, a fund manager and a main character in *The Big Short* (Lewis, 2011), who set up his office far away from the financial centers and turned off Bloomberg news updates to maintain his natural state of being an outsider. By reducing exposure to the norms, incumbents, and noisy information, a strategist is more likely to judge an opportunity based on its merit rather than social norms. While interdependency barriers can be attenuated by being an outsider, outsider status creates other challenges, such as understanding what resources are misevaluated (i.e., learning barriers). Thus, strategic isolation can be a more general approach for those who aspire to exploit others' mistakes.

Overall, this discussion suggests that a strategist should reduce dependency before exploiting a behavioral opportunity by translating under- or overvalued resources into unambiguous superior performances, searching for opportunities in remote networks where local interdependency is strong for insiders but weaker for the strategist and reducing exposure to potentially biased information and evaluators.

How to Learn More Effectively than Others

To overcome learning barriers, a strategist can conduct counterfactual experiments to avoid being fooled by misleading data. For example, high performers can continue performing better due to strong self-reinforcing mechanisms rather than due to high or improved competence. One way to test this alternative hypothesis is to remove the resources high-level performers have (or give the inferior performer a second chance) and examine how performances change. This does not mean that high-level performers should be punished or that low-level performers should be rewarded. Our point is that statistical regression as well as misestimations cannot be detected or falsified if the observations are misleading unless an experiment is conducted that disentangles confounding variables. To disentangle self-fulfilling prophecies from skill explanations, a strategist can either (1) abstain from giving extra resources to better performing people or (2) give resources to those who perform poorly. By observing the outcome and comparing them with a control condition in which people who do well are given extra resources, decision-makers can estimate the role of skills and self-fulfilling prophecies. Such experimentation is costly but may generate non-intuitive insights that can overcome learning barriers.

More generally, overcoming learning barriers usually requires a strategist to have access to superior data relative to rivals. The estimation can be self-defeating if the data are already polluted by self-fulfilling or selection processes. Strategists who aspire to exploit others' mistakes should start looking for contexts in which acquiring superior data relative to rivals is feasible. For instance, the insurance giant Progressive collected more than eleven categories of age information (among other details) in order to refine their proprietary pricing algorithm (Porter & Siggelkow, 1997). As a result, they were able to quote individualized and customized premiums by differentiating in a fine-grained manner according to the risk profile of each individual. Such a deliberate attempt to acquire more data was seen as one of the crucial reasons behind their rapid rise in the 1980s in the non-standard segment of the auto insurance industry.

Nevertheless, data availability per se is not necessarily associated with attractive behavioral opportunities. If a large volume of data is available to many, behavioral opportunities are unlikely to persist because many strategists can identify and take advantage of them. Behavioral opportunities are more likely to persist in settings with limited data and where the presence of many confounding variables makes it challenging to accurately estimate the magnitude of regression to the mean. Overall, this suggests that the advantage of sophisticated strategists is greatest in moderately complex environments where acquiring data and effective learning is difficult but not impossible (Schoemaker, 1990). Fortune favors the strategists who can creatively collect and analyze the data in order to see what others fail to see.

Since access to superior data is not always within a strategist's control, an additional way to search for attractive behavioral opportunities is to focus on non-intuitive phenomena. For example, the strong version of luck is more counterintuitive because it goes against people's common-sense inferences of monotonicity. Searching for non-monotonic kinks can lead to more promising opportunities because they are least expected by others. Strategists could collect consecutive performances data, measure the context-dependent regression effects, and identify whether the effects are strong enough to generate non-monotonic performance associations. For example, the strong version of luck is more likely to occur in smaller industries (where smaller sample size implies greater unreliability in performances), more volatile industries (where performances are more sensitive to factors beyond managers' control), and more complex industries (where interdependent systems are more sensitive to small shocks). To laypersons, non-monotonicity is counterintuitive, and therefore they are more likely to invent causal explanations for why it occurs. Strategists can then search for the contexts in which these false explanations imply flawed and consequential mistakes. Finally, strategists could also recruit and work with the naïve (March, 1991), i.e., outsiders who are not aware of potentially suboptimal decision heuristics or colorful but misleading stories of why performances are regressive.

Overall, this discussion suggests that a strategist can overcome learning barriers more effectively than rivals by conducting counterfactual experiments, acquiring superior data in moderately complex environments, and focusing on unintuitive phenomena.

Summary

It is important to point out that both the behavioral barriers and the associated strategies to overcome them are interrelated. For example, hiring the naïve can help identify an exploitable bias and remove both barriers: these outsiders are less likely to be aware of the conventional wisdom and social norms of a given context, so they are more likely to identify, learn about, and act upon a potential bias. While these behavioral barriers are not mutually exclusive, each of these two barriers is built upon a distinct body of literature. For instance, searching for behavioral opportunities starts with identifying a particular bias and this is largely informed by the behavioral decision theory literature (Kahneman, Slovic, & Tversky, 1982; Todd & Gigerenzer, 2012); the learning barriers are based on the organizational learning literature (Cyert & March, 1963); the interdependency barriers come from ideas around coordination, conformity, and social evaluation in institution theory (Asch, 1955; Benner & Zenger, 2016; Correll et al., 2017; DiMaggio & Powell, 1983; Oliver, 1991, 1997; Suchman, 1995; Zuckerman, 2012). Even though these related ideas come from distinct sociocognitive disciplines, we believe that they constitute, collectively, a coherent behavioral framework for competitive advantage.

While our theory is context-independent, its application has to be context-dependent. That is, a strategist needs to understand the nuances of how behavioral forces operate and interact in a specific context. Also, our theory operates across different levels of analysis. The barriers we discussed can be applied to decisions by an individual or organization (e.g., failure of learning regression to the mean) but they can be between individuals and organizations (e.g., failure of coordinating with stakeholders when pursuing a unique resource). These behavioral forces together determine how attractive a behavioral opportunity is.

Figure 3 presents a decision flowchart in order to evaluate when an opportunity based on a bias (such as the misattribution of luck) is attractive and the strategies one can pursue to overcome the behavioral barriers aforementioned. We are not arguing that strategists should always pursue behavioral opportunities; whether this is advisable depends on a strategist's circumstances and risk appetite. Behavioral opportunities are contrarian in nature and tend to be risky: like searching for a needle in a haystack. Our goal is to provide a theory of which haystacks the needle could be found in, which simplifies the search but does not eliminate risk. More generally, our ambition is to outline an alternative source of profit and opportunity for strategists to consider as an option. If a strategist wants to pursue this option, she should start a search for a potentially exploitable bias by examining how this bias can lead to systematic mispricing of strategic factors and by developing exploitation strategies (e.g., Sections 2 and 3 of this paper). If the answer to the first question is negative, this means that behavioral opportunities may exist but there may be no feasible strategy to exploit them.

Insert Figure 3 about here

If the answer to the first question is positive, the strategist could move on to the second step to examine whether the strategist could overcome the interdependency barrier. The opportunity is more likely to be exploited when the strategist could transform the mispriced resources into something others can value or the strategist could position herself to become less dependent on others. If the answer to the second question is negative, the interdependency barrier implies that the social cost may overwhelm the economic benefit of exploiting this identified opportunity for this strategist.

If the answer to the second question is positive, the strategist could examine whether she could overcome the learning barrier by developing counterfactual experiments. The focus should be on unintuitive phenomena such as non-monotonic performance associations. If the answer to the third question is negative, the strategist may get stuck in learning traps like others or may only enjoy a short-lived advantage because others can soon learn and imitate the strategist's approaches. If the answers to all three questions are positive, it is likely that an attractive opportunity does exist and that the strategist is both analytically and socially savvy enough to identify and exploit this behavioral opportunity. Fortune favors this strategist for being informative, insightful, and insensitive.

6. CONCLUSION

Decades of research in cognitive, organizational, and social sciences show that people tend to make systematic mistakes. Instead of de-biasing strategists as conventional theories suggest, we outlined a framework to guide strategists in their search for behavioral opportunities arising from these predictable mistakes, particularly those resulting from the misattributions of luck in performances. We first outlined *where* these misattributions of luck are the strongest (see Figure 1) and discussed *what* the possible exploitation strategies are. Next, we discussed the scope conditions of these opportunities and exploitation strategies by utilizing behavioral theories to predict rivalry (see Figure 2): opportunities from misattribution of luck are more attractive *when* they are protected by strong barriers that deter learning and being contrarian. Finally, we discussed *how* a strategist could overcome these behavioral barriers more effectively than rivals. The decision flowchart (Figure 3) summarizes the way we address these "where, what, when, how" questions regarding opportunities from misattributions of luck. Searching for profitable opportunities is like searching for a needle in haystacks. Our theory makes the search more effective by guiding strategists to start with the haystack in which attractive behavioral opportunities are more likely to exist and the strategists are more likely to overcome the behavioral barriers associated with the opportunities. Our theory shows how well-known ideas from disparate disciplines can be woven together into a coherent and novel theory for strategic advantage.

Is our theory only applicable in contexts with large volumes of data available, such as sports or the financial markets? We do not think so. Whether regression to the mean occurs or not does not depend on data availability, but regression to the mean is more easily identified and measured in large data settings. Hence, the best illustrations are from such settings. Even in a setting with limited data, however, a manager should expect that sales will be lower next year if they were exceptionally high this year. Limited data make it more difficult to accurately measure the magnitude of regression to the mean. This makes it riskier to exploit such a potential opportunity, but also increases the chances that others have missed it, because detecting this opportunity requires theoretical insight into when regression to the mean occurs instead of only relying on empirical analysis of past data. Studies show, however, that even in large data settings, such as sports and finance, managers and professional forecasters fail to properly take into account regression to the mean (De Bondt & Thaler, 1985; Denrell & Fang, 2010; Huberts & Fuller, 1995; Kahneman & Tversky, 1973; Massey & Thaler, 2013). If biases can persist in controlled experiments, sports, and financial markets where data are relatively cheap to acquire and easy to process, we believe that opportunities are even more abundant in more limited data settings. But our theory also predicts that it is more risky to exploit these opportunities due to limited data. It is up to the strategists to evaluate whether they have a sufficiently robust strategy as well as the risk appetite to exploit these opportunities.

More generally, our theory also provides an alternative answer to the question, where does superior profit come from? Prior studies have proposed various answers for addressing this key question in strategy. For example, superior profits can result from having a structural advantage (Porter, 1980; Puranam & Vanneste, 2016) or controlling valuable, rare, inimitable, and non-substitutable (VRIN) resources and capabilities (Barney, 1991; Teece, Pisano, & Shuen, 1997). However, two puzzles remain regarding these popular and widely diffuse answers to the sources of superior profit. The first puzzle is a theoretical one: if the relationship between controlling these strategic factors and having superior profit is well known, the cost of acquiring these factors should reflect their value (Barney, 1986). This in turn implies competitive parity—failing to acquire these factors means disadvantage but controlling them cannot be sufficient for generating abnormal return. The second puzzle is an empirical one: large firms were regularly disrupted by entrepreneurs who had neither a structural advantage nor VRIN resources (who should not have entered in the first place according to conventional strategy frameworks). These puzzles imply that an alternative strategy theory is needed for explaining the source of superior profit without resorting to random factors such as luck, serendipity, or preadaptation (Barney, 1986; Cattani, 2005; Denrell et al., 2003). Our theory suggests an alternative, behavioral source of superior profit that complements existing strategy frameworks: superior profit can result not only from economic barriers that deter rivals' entry, but also from behavioral barriers that deter learning and being contrarian. Systematic biases in fact illuminate an important, overlooked source of heterogeneity in firms. Our paper can serve as a template for future research to explore when other known biases may create behavioral opportunities and how strategists could identify and exploit them systematically.

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FIGURES AND TABLES

FIGURE 1
Two Versions of the Impact of Luck on Predictions

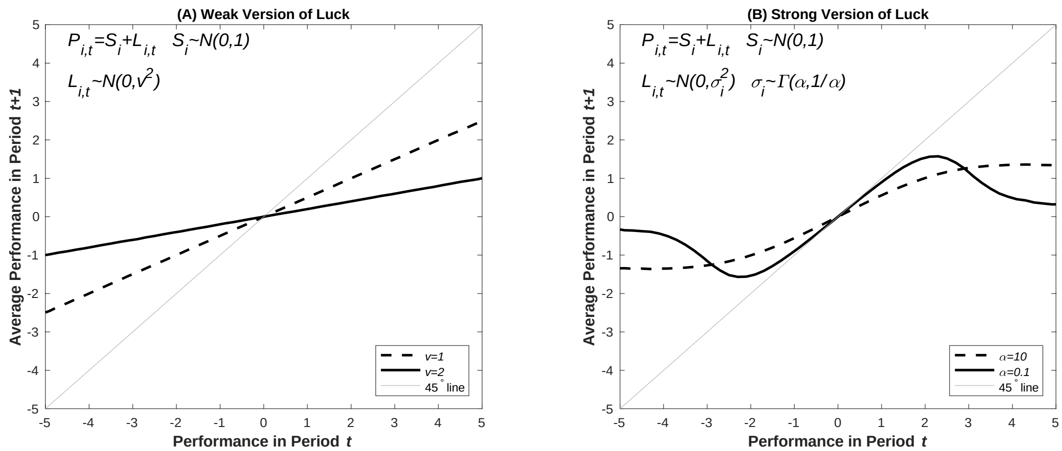

FIGURE 2
The Source of Profit from Exploiting the Common Misattribution of Luck

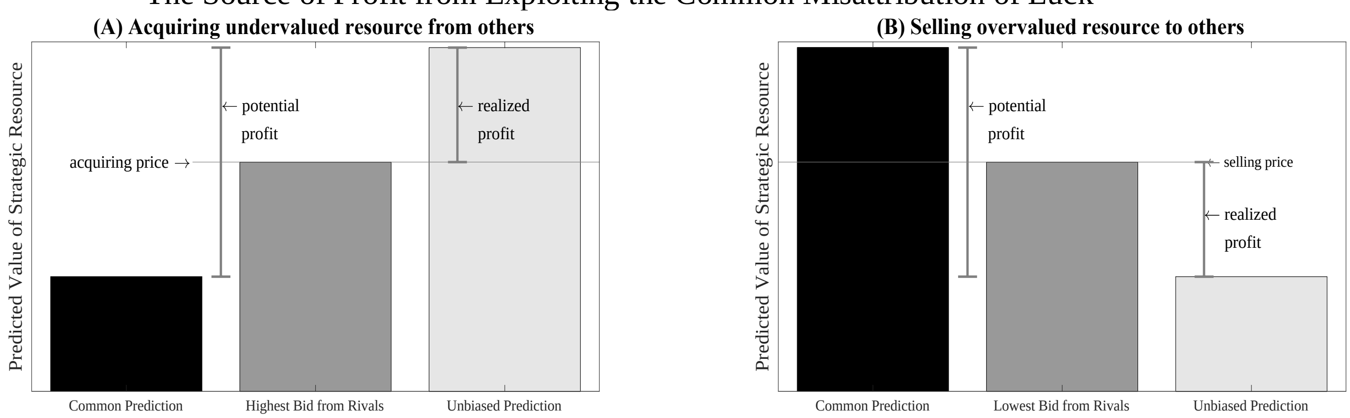

FIGURE 3
A Decision Flowchart

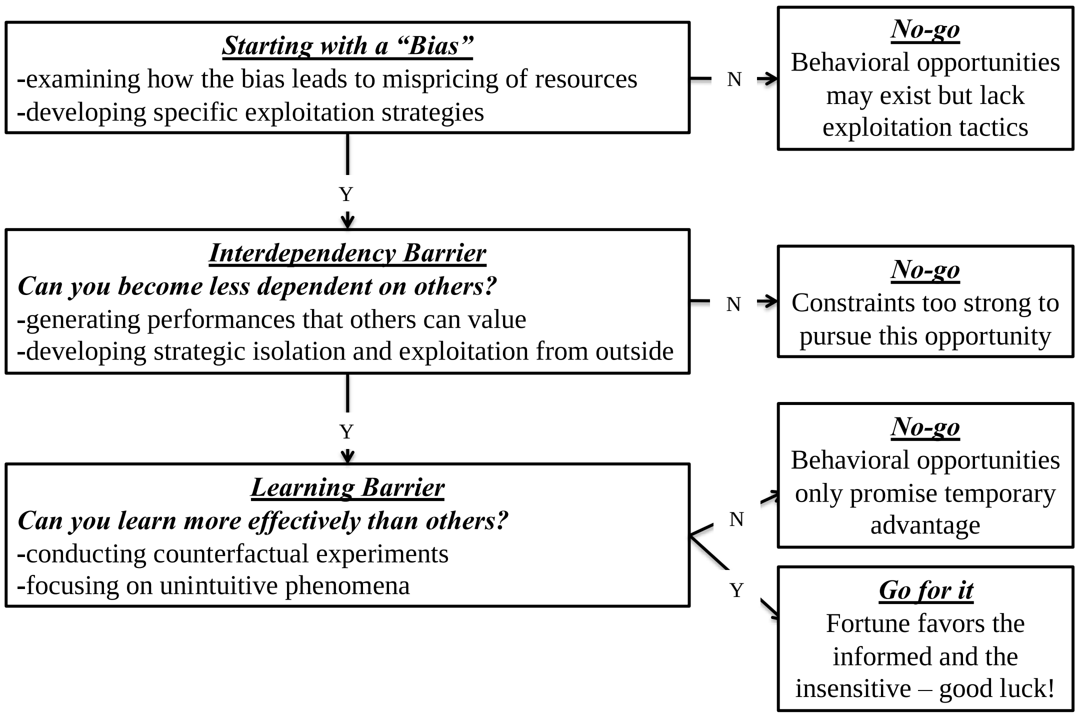

TABLE 1
Exploitation Strategies Under the Weak Version of Luck

		Naïve Strategist *B*…	
		overestimates resource *R*	**underestimates resource *R***
Informed Strategist *A*…	**owns resource *R***	*Proposition 3A: A can profit by selling B the resource R and its complementary resources.*	*Proposition 3C: A can profit by acquiring from B the complementary resources to R.*
	does not own resource *R*	*Proposition 3B: A can profit by selling B the complementary resources to R.*	*Proposition 3D: A can profit by acquiring from B the resource R and its complementary resources.*