The Illusion of Success and the Nature of Reward

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Abstract: Many successful activities and outcomes benefit from strokes of luck. Moreover, humans are over-confident and tend to confuse luck for skill (“Heads I win, it’s skill; tails, I lose, it’s chance”). Where success derives in large part from luck, it follows that there is an outsized propensity towards rewarding luck rather than merit (skill and effort). This rewards a culture of gambling, while downplaying the importance of education, effort, qualitative process and persistence. This may also be one of the factors explaining excessive risk-taking in activities, such as finance, dominated by stochastic processes. To address this, we propose three different ways to classify reward-based success: (i) outcome based reward; (ii) risk-adjusted outcome based reward and (iii) prospective reward. With the goal of better matching merit and reward, we emphasize the need to navigate into the future using the framework of complex adaptive systems, decomposing any action into five steps: observe, decide, execute, challenge and explore. We present a review of several human endeavors analyzed through the lens of these measures and propose concrete solutions to restrain from rewarding luck while encouraging skill and effort by focusing on process. Applications and recommendations are suggested for finance, tax policy, politics and science.
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1. Introduction

We like to think that our successes result from our efforts, competence, tenacity, will power, talents..., in a word, from our merit. Success is thus the fair consequence of our labor, as one would wish in an equitable meritocratic society. In fact, decades of research show that luck can often play a dominant role and disentangling the relative contributions of skill and luck in success is hard. These questions have been investigated in a variety of disciplines, including complex systems, cognitive sciences, behavioral economics, political sciences, finance, business, management, sports, gambling... There have been many exceptional and original contributions to the academic literature (see for example early works of Merton, 1961, Langer, 1975, Montroll and Schlesinger, 1982 and Dorner et al, 1990). The main results of these studies have been made accessible to a broader public in a number of best-selling books (such as Taleb, 2005; Mauboussin, 2012; Tetlock and Gardner, 2015; Kahneman, 2011; Frank, 2016).

How skill and luck contribute, each separately, to success depends preliminary on the rules of the game. In a regular environment, with clear and simple rules, and which provides sufficient time and opportunity to learn through trial-and-error, skill will be the principal contributor to success. On the other hand, when irregularity or complexity are dominant, or, when the rules of the game are fuzzy or convoluted, or, when there is not sufficient time to learn, luck will be the dominant factor. A practical way to compare the attribution of luck versus skill for different games can be done by positioning them on the skill-versus-luck continuum (Mauboussin, 2012). For each activity, the variance of the actual observations is compared with the variance of the results that would be seen if the game was purely run by chance. For example, the variance of the percentage of winnings of each soccer team in a national soccer competition is compared with the variance if the outcome of each game was the result of coin-tossing. The ratio of the variance governed by pure luck to the observed variance defines the position of the activity on the skill-versus-luck continuum. Figure 1 shows such a ranking of different activities. Chess and roulette are on the opposite sides of the spectrum. If you apply a random strategy in roulette, you will not outperform or underperform with respect to your fellow players. However, if you do the same in a game of chess, you will most definitely lose. We should stress that this approach to rank skill-versus-luck is a first step but is not perfect, as variance is not necessarily a correct indicator due to mixing up competitiveness of a league and resulting intransitivity cycles with luck.

![Fig. 1: Different activities in sports, investments and gambling, ranked on the skill-versus-luck continuum (taken from Mauboussin, 2012).](image)

The ubiquitous failure to adequately apportion success to skill versus luck leads to an unintended consequence within a society obsessed with success. Because, in general, success is the outcome that is rewarded for activities on the left-end side of the scale in figure 1, rewarding success implies remunerating luck. For activities on the right-end side, rewarding success is adequate, since skill, success and reward are highly correlated. Indiscriminately rewarding success regardless of the position of the activity on the skill-versus-luck-continuum
thus leads to an incentive system that presents the danger of promoting gambling, risk-taking and deterrence of genuine efforts. In the many activities where luck is the principal cause for success, rewarding success is like rewarding luck, hence, the incentive model becomes nothing else than a noise amplification mechanism.

If incentives reward success, and success often comes from luck, is this the society that is desirable? Could we rethink our incentive structures and give more weight to processes and skills, instead of to success? In this paper, we will open Pandora’s box and challenge the accepted incentivization model of rewarding success.

In the following part, we will go deeper into some mechanisms that drive and even exacerbate the problem outlined above, such as the non-linear dynamics of increasing returns leading to lock-in effects and winner-take-all markets, asymmetric information and dishonest signaling inducing adverse selection, excessive risk-taking behavior in the genetically endowed male population, the illusion of control, and data-snooping. After this elaboration, we will plug the skill-versus-luck continuum into the broader dynamical framework of an adaptive strategy. This will allow us to properly define the fundamental components that are part of our research question: skill, rules, conditions, conventions, attitude, efforts, merit, ..., luck, success and reward. Taking this step back to define the archetype process will help us to articulate our challenge more precisely. In the final part, we will discuss three specific cases of how success versus kill is evaluated: by taking a snapshot view in the present, so by simply rewarding success, by carefully analyzing the past and present, so by rewarding the process based on quantitative historical performance, or, thirdly by assessing the past, present and future, so by rewarding the process based on forward-looking and learning capabilities. These three complementary cases characterize the hierarchical methodology that we propose in order to adapt the nature of reward in our society and to skew this towards a rewarding of processes and skill instead of luck.

Notwithstanding the large amount of works on skill versus luck, to our knowledge, the disentanglement of skill and luck has, up to now, never been linked to the process of reward and incentivization. We will explore how reward is closely linked to general conventions in our society and how the current conventions have pushed the economic system into a sub-optimal situation. We will challenge these conventions and suggest that a better allocation of resources and skills through a different reward model may be possible. We will conclude that rewarding success, while the “natural” default method for lack of better ones in the presence of high monitoring costs, is not ambitious enough, we can do better.

2. Mechanisms

2.1 Winner-takes-all: a pervasive mechanism for luck in success

We live in a strongly connected society where ideas, opinions, new technologies, fashion, music, and so on, are adopted through viral interaction in social networks. Imitation and social influence are the key elements in a positive feedback mechanism that creates a condition of increasing returns and an effect of cumulative advantage for the winners. As explained by Brian Arthur (1989) in his seminal paper on increasing returns and lock-in effects, when two or more economic objects compete under increasing returns, insignificant events or minor differences in the initial conditions may by chance give one an initial advantage. As a result, it may improve more than the others and appeal to a wider proportion of potential adopters. Through the feedback mechanism of adoption (which makes the product valuable solely on the basis of its extended use in the social network) and improvement, the agent that by chance gained an early lead may eventually corner the market and totally lock out the competition. In
the end, this becomes a winner-take-all market where the success, or the reward of the winner, is in no way related to the initial conditions, or to the skills of the different economic agents. Arthur concludes: *To the degree that the technological development of the economy depends upon small events beneath the resolution of an observer’s model, it may become impossible to predict market shares with any degree of certainty* (Arthur, 1989). In other words, the mechanism of increasing returns is associated with strong (stochastic) path dependency. This insight has practical implications for many activities in our modern society such as financial planning and budgeting, economic forecasting, marketing, design, fashion, research and development, trading, investing, mergers and acquisitions, private equity, venture capital, music, film, art and so on. Most of these activities, if not all, should be ranked to the left side of the skill-versus-luck continuum (figure 1). This leads to winner-takes-all markets where superstars are rewarded disproportionately, just because they have been lucky.

Winner-takes-all markets are part of a more general class of phenomena called ‘Frozen accidents’ (Gell-Mann, 1994). According to the physicist, Nobel prize winner and co-founder of the Santa Fe institute, Murray Gell-Mann, the character of our universe and the nature of life are the result of chance events and the effective complexity of the world receives only a small contribution from the fundamental laws.

Tullock contests provide an interesting set-up to control and study the relative role of effort versus chance in winning a prize (Tullock, 1980). In a typical situation, with the goal to win a prize, two or more players expend costly resources whose magnitudes determine their probability of winning the prize. In general, the total payoff of a player can be a function of prizes, own effort and the effort of the rival (Chowdhury and Sheremeta, 2010). By changing the competitiveness parameter, cost of winning and spillover from losing, one can tune from random allocation to winner takes all. Unsurprisingly, one finds, for instance, that efforts are deterred if the winning prize is not large enough in comparison with the expended efforts. In that case, the players prefer to let pure chance decide the outcome. Also, if the positive externality gained by losing increases relative to that of winning, then the players will spend less effort to win the contest, which is reminiscent of R&D contests in countries where property rights are not well protected. A more important insight is that small parameter modifications may lead to substantially different optimal effort levels and thus of sizeable changes in the role of chance in getting the prize.

2.2 Adverse selection

In any communication between individuals, there is a degree of asymmetry, where one party has more or better information than another. When there are conflicting interests, or when incentives are not aligned, false signals may be disseminated. The origin, the functioning and the consequences of this ‘dishonest signaling’ (one could simply call it cheating or bluffing) is an established research subject in evolutionary biology.

In economics, the mechanism was brought to the attention of the wider research community by George Akerlof (1970). He developed a thought experiment based on a second-hand car market consisting of both good-quality cars and so-called ‘lemons’, which is lingo for a crappy second hand car. When sellers and buyers have asymmetric information about the quality of a good, buyers will automatically correct their bid price based on an estimation of the fraction of ‘lemons’ in the market and the value of ‘lemons’ vis-à-vis good-quality cars. This bid price will be somewhere in between the value of a good car and a ‘lemon’. Sellers, on the other hand, having superior information, will set their ask price higher than the bid price in case of a good car, and lower than the bid price for ‘lemons’. As a consequence, sellers of high-quality goods will exit from the market leading to an adverse selection of low-quality goods. This
adverse selection mechanism, based on private information, may lead, according to Akerlof, to the malfunctioning of markets.

George Akerlof’s initial work was soon picked up by Michael Spence (Spence, 1973), who studied education as a signal in the job market and Joseph Stiglitz, who analyzed what uninformed agents may do to improve their outcome in a market with asymmetric information (Rothshild and Stiglitz, 1976). Stiglitz’s work with Grossman, in 1980, on the hypothesis of efficiency in financial markets led to the Grossman-Stiglitz paradox: if a market were informationally efficient, so that all information is reflected in market prices, there would be no incentive to acquire the information on which these prices are based (Grossman and Stiglitz, 1980). Hence, an informationally efficient equilibrium does not exist as any evolution towards such an equilibrium would automatically disincentivize any economic agent to acquire further knowledge, thus pushing the market towards less efficiency.

In 2001, George Akerlof, Michael Spence and Joseph Stiglitz received the Nobel prize in economics for their work on asymmetric information. The importance of their work for the present paper is that the difficulty to disentangle skill and luck is further aggravated by the fact that ‘signaling of success’ has a strong component of asymmetric information. Success due to luck may be known to the recipient aware of her limited skills, but not to the observer. Senders of ‘success signals’ have more information than receivers. These differences can drive out good quality and lead to adverse selection.

Chance in success may also arise, not from the environment itself but, from how credit is given to one’s work. This can result from asymmetric information as previously discussed, which in the extreme may lead to reward merit in a purely random fashion. Another mechanism is group level scoring, which tends to water down individually relevant information, leading to the potential destruction of cooperation in response to inequitable rewards (Duca and Nax, 2018): as others unfairly reap the benefits of one’s efforts, efforts disappear and chance strives.

2.3 Male-male competition and evolution

All living individuals share common ancestors, which can be dated back along specific ancestry lines using genetic methods. In this way, the Most Recent Common Ancestor can be identified as the human being from which all others directly descended. The age of this genetic singleton is called the Time to the Most Recent Common Ancestor (TMRCA). Genetic studies have shown that the matrilinear TMRCA is roughly twice as old as the patrilinear TMRCA. Based on these findings ‘Eve’ should have lived 170-240 thousand years ago, whereas ‘Adam’ would have wandered paradise’s pastures 46-110 thousand years ago (Baumeister, 2010). In other words, females have propagated their genes across much larger spans of time than males, who are faster “forgotten” in the battle of genetic transmission.

Using Agent Based Models, Favre and Sornette (2012) demonstrated that the strong unequal biological costs of reproduction between the two genders is the likely underlying explanation of unequal TMRCA. Over the course of human evolution, the genetic reproduction of mothers comes at a much higher cost than for fathers. As a consequence, females engage in choosy selection, preferring a fitter, alpha-type of mate to spend their precious and scarce reproduction potential. The result is strong male-male competition and high risk-taking behaviors, each male striving to signal as an alpha in order to be selected by the choosy females for genetic reproduction. In the largest part of human pre-history and history, most males failed, so that the trace of their genes faded away much more rapidly than those of females, explaining the factor 2 in the ages of the TMRCA (Baumeister, 2010; Favre and Sornette, 2012). Importantly, the high-risk taking propensity of males, especially young males in the early years of reproduction, has survived in modern humans. Thus, even in the absence of problematic
incentives, men have evolved to take much more risk than females: in a sense, "badly" behaving males caused by females being ultra-picky.

Gender competitive-related differences are of particular importance in finance. Coates et al. (2010) document that success in financial markets increases the testosterone level in young male traders. As chronically elevated steroids may promote irrational risk-reward choices, they suggest that *irrational exuberance and pessimism observed during market bubbles and crashes may be mediated by steroid hormones*. As a consequence, more gender diversity in the trader community should have a positive effect on the stability in financial markets.

Favre and Sornette (2012) conclude: *... we propose that a high male-male competition for reproductive success that has been permeating the history of modern humans ... has contributed through gene and culture coevolution to create gender competitiveness-related differences ... These considerations raise the question of how to adjust our cultures and/or design society rules in order to match better the evolutionary-based inherited human traits described above and the requirements of the modern ages.*

In this paper, we propose such a cultural adjustment, by shifting incentivization from success-driven towards process-driven, considering and correcting for risk-taking behavior. We will come back to this in section 3, where we build a toy model to better understand how to favorably select merit by correcting for risk-taking behavior.

2.4 Heads I win, it’s skill; tails, I lose, it’s chance

Even though people are fully aware of the concept of chance in a game, they still behave as if they are in control. It is a familiar sight that, throwing dice, players behave as if they were controlling the outcome of the toss, being careful to throw softly if they want low numbers, throwing hard for high numbers. Ellen Langer referred to this phenomenon as 'the Illusion of Control', that is an expectancy of a personal success probability inappropriately higher than the objective probability would warrant (Langer, 1975). She based her insights on experiments conducted on individuals in chance situations and concluded that 'the illusion of control' arises from the fact that people want to be in charge of their environment and avoid the anxiety arising from a temporary loss of control. This includes the control over chance events, where people are convinced that they have the ability to ‘beat the odds’, the more difficult a problem is, the more competent one feels ... the greatest satisfaction or feeling of competence would therefore result from being able to control the seemingly uncontrollable.

Using computer simulated environments, Dietrich Dorner went beyond chance situations and investigated how humans make decisions in complex fields of reality. His scenarios included non-linear dynamics, network dependencies, time-delays and oscillations resulting from feedback processes. In a paper entitled ‘the Logic of Failure’, Dorner et al. (1990) explain that people do not want to be confronted with the consequences of their actions. In that way, they can maintain an 'illusion of competence'. Dorner et al. call this acting 'ballistically'. Without self-reflecting examination and critique, individuals delude themselves in having solved problems merely by means of their action without any need to look back and check for the consequences and the effectiveness of their deeds.

Examining success and failure, most people hardly look beyond the superficial, the obvious, what is right in front of their noses. As such, they attribute desirable outcomes to internal factors, but blame externalities and bad luck, for failures; they are hard-wired to over-attribute success to skill and to underestimate the role of chance. Langer refers to this as the ‘just world’
hypothesis, where good things happen to people who do good things, bad things happen to people who do bad things.

2.5 Data snooping

Focused on success, we accentuate positive results without careful statistical consideration of the fraction of false positives in the dataset. This bias makes the investment industry thrive. Barras et al. (2010) studied the historical performance, from 1975 to 2006, of 2076 actively managed U.S. open-end, domestic mutual funds. They developed a statistical model to estimate what fraction of these funds had a positive alpha, a fund’s measure for success, based on true skill, using a methodology to explicitly correct for luck. They found that 75.4% were zero-alpha funds, with stock-picking skills just sufficient to cover trading costs and expenses, 24% were found to be unskilled, meaning that the stock-picking skills were insufficient to cover the fees, and merely 0.6% were found to be skilled funds. Besides the fact that the number of truly skilled advisers was found to be statistically indistinguishable from zero, the study found that a quarter of the funds actually destroyed value for their customers and managed to continue doing so for a period of 12.7 years on average. The authors attributed this inefficiency to the alleged non-sophisticated nature of many investors. But even sophistication does not guarantee the ability to distinguish skill from luck, or phrased differently, to distinguish true positive from false positive results. In 2012, researchers from Amgen, an American drug company, tried to reproduce the successes of 53 ‘landmark’ cancer papers. It turned out that they could only reproduce the results of six, which is merely 11% (Economist 2013, Begley and Ellis 2012, Baker 2016). This is consistent with the findings of a team at Bayer HealthCare in Germany, which reported that only 25% of published preclinical studies could be validated to the point at which projects could continue (Prinz et al., 2011).

A fundamental explanation of this ‘crisis of reproducibility’ is a deficient knowledge of statistics among researchers. An example is the misuse of p-values as the ‘gold standard’ of statistical validity, which overlooks prior judgements of realism (Nuzzo 2014, Leek and Peng 2015, Baker 2016, Wasserstein and Lazar 2016). The level of statistical significance of a claimed discovery, often taken indiscriminately at 95%, should be adapted to how much it fits with existing theory and understanding, and how surprising or even disrupting it may be. In a meta-study on the reproducibility of research claims, the epidemiologist John Ioannidis (2005) concluded that, in modern research, false findings may be the majority or even the vast majority of published research claims.

The well-known phenomenon of data snooping (or overfitting) adds to the difficulty of detecting true positives. Data-heavy disciplines, in particular, are prone to these types of errors. A telling example was given by a managing director in an interview with Business Week explaining that, based on extensive data analysis, the single best prediction of the S&P 500 stock index was butter production in Bangladesh (Sullivan et al. 1999, Coy 1997). Now that big data, artificial intelligence and machine learning are being hyped as resources and tools in scientific research as well as in business, the fight against data snooping, and against lucky successes that do not imply causation, is a never-ending quest, which requires using the right statistical techniques (see e.g. Zweig 2014, Lo and MacKinlay 1990, Sullivan et al. 1999, Bailey et al. 2015 and White 2000), as well as being disciplined.
3. How to play a game

3.1 General framework

Any activity or game is based on a set of rules. These not only define the kind of resources that are required to play, like a game of chess requires different skills than a soccer match, but also how strong the role of randomness will be. These rules define the position on the skill-versus-luck continuum. As we explained in the introduction, it is useful to compare different human activities on this scale. However, this only gives a static and one-dimensional cross-section of a much richer, dynamical and multi-dimensional process.

In fact, playing a game may be to enjoy, but also to win as well as to exert one’s talents…¹. This is done by working out a strategy, which in itself is a decision on how to use the resources (or the skills) that are available to the player, constrained by the rules of the game. Figure 2 gives a schematic representation of how a game can be played. The grey box is the core of the process. When the game starts, a player will execute a strategy and will bring resources into use. The effectiveness, or fitness, of this decision, will be carefully judged by the player and, based on the result, an incentivization mechanism will feed back through the reward model. This makes the strategy adaptive so that the use of resources is dynamically tuned to the outcome of the game.

Fig. 2: A game is played by applying a strategy. This takes into consideration the rules and the position of the game on the skill-versus-luck continuum. The perception of fitness of the strategy is subject to cultural conventions or norms, which are endogenous, and the effectiveness of the strategy changes with altering exogenous environmental conditions. The process is made adaptive through a feedback mechanism of reward, which changes the use of resources dependent on the fitness.

¹ Please note how the concept of the skill-versus-luck continuum only gives static information on an aggregated level. It does not take into consideration the fact that the game actually needs to be played by individual players, nor does it explain how this game may be played or how a strategy may be optimized.
The process (grey box) has three major inputs: the rules of the game and its position on the skill-versus-luck continuum, the exogenous environmental conditions and the endogenous cultural conventions, or norms.

### 3.2 Environmental conditions
The environmental conditions are external factors. This means that they are not at the discretion of the player but may nevertheless strongly impact the fitness of a strategy.

When the environment is stable, or when any change has a negligible effect on the state of the game, the process can be fully optimized by “looking backward” at the past performance, it can be described statistically and can be managed quantitatively. For such processes, it is effective to use inductive scientific reasoning. This means that general conclusions can be drawn from specific, individual, historical cases. The reward of such processes should be based on how well all the different aspects of past performance are taken into consideration.

When the environment is non-stable, a different modus operandi is needed as there is no continuity that allows for robust statistical descriptions and quantitative management. In such cases, a deductive approach is more effective. This means that specific events are deduced from general assumptions and the system is managed through the use of toy models, stress testing and scenario generation, the introduction of redundancy, the qualitative assessment of resilience, the use of heuristics and management tools such as checklists and so on. In contrast to quasi-stable processes, the past is not the driving force, but a resource from which selective information can be extracted to anticipate future scenarios. These can include not only possibilities that have actually materialized in the past, but also events that have never occurred. Seligman et al. (2013, 2016) conjecture that prospection is the central organizing feature of a human being’s perception, cognition, affect, memory, motivation, and action. According to the authors, human beings as a species should not be named *Homo Sapiens*, which means ‘Wise Man’, as this is arguably less a description than an aspiration, but *Homo Prospectus*, ‘Forward Looking Man’ for whom consciousness is the generation of simulations about possible futures.

Jeff Hawkins (2004) proposes a neuro-biological foundation for our inclination for predicting the future, hypothesising that the basic brain processing principle is a feedback/recall loop that involves both cortical as well as thalamus and hippocampi participations to develop recognition and prediction in a bi-directional hierarchy: this “memory-prediction” theory claims that our brain is thus constantly trying to predict and then compare, predict, compare, learn, adjust, predict and so on. In related thinking, Karl Friston et al. (2006, 2012) posit that biological systems strive to minimize the differences between expectations and sensory perceptions (Perrinet et al., 2014).

In a non-stable environment, we thus propose that processes should be rewarded according to their ability to look into the future and navigate into the future, following a kind of Bayesian inference model of error reduction through learning and control in a feedforward loop.

Finally, it should be mentioned that both stable and non-stable processes may co-evolve in one single dynamical process. In biological evolution, for example, there is a progressive accumulation of small so-called “neutral” mutations that have no apparent effect on the fitness due to the huge redundancy of metabolic chemical reactions. Then, when a threshold is reached, the last minor mutation triggers a cascade of changes, which may lead to a new species (Wagner, 2015).
3.3 Cultural conventions

Cultural conventions are internal factors. Referring to our scheme in figure 2, they have an influence on how the fitness of a strategy is perceived and how it is translated into a reward model or an incentivization scheme. Any change in fitness will result in a change in reward, which in itself is a change in strategy, because it implies a different use of resources. As norms are endogenous, it is up to the player to decide whether or not to apply them.

We conjecture that, when economic agents play following a process as depicted in figure 2, both the fitness calculation and the reward model are strongly influenced by these cultural conventions, even though it is at the player’s discretion to decide how much to adopt them. Some examples of such conventions are e.g. the time frequency used to sample fitness and adapt the strategy, whether the fitness is assessed at the individual or an aggregated level, how the role of luck is discounted in the award, if externalities are taken into consideration or whether overselling and signaling can be properly accounted for (Dorner, 1997).

By the very nature of success, there is a myopic focus on it, without considering the relative contributions of skill and luck. Because assessing the true merit is difficult, cost- and time-consuming and prone to errors, success is the easy-to-use default measure of quality and skill, at the cost of severe potential misrepresentation. Consider the case of critical industries, in which accident or not is largely a 0-1 outcome. The absence of accidents is often deemed to reflect an adequate and successful management. However, cases often exist where there was a high probability (say 10%) of an accident that was avoided by luck. If such events are not penalized, a culture of over-confidence and mis-attribution leads to the degradation of governance and of risk management. This process explains the maturation mechanisms underlying many catastrophes (Chernov and Sornette). As an illustration, this is one reason why the nuclear accident of Three Mile Island, 1979, can be thought of as a major accident, notwithstanding its quasi-absent release of radioactive substances, because there was a significant chance of a large release (Sornette et al., 2018). These considerations apply to many other industrial sectors.

Due to the nature of many economic activities, and their position in the skill-versus-luck continuum, this often results in rewarding randomness on an individual level and a sub-optimal use of available resources on a global and long-term level. As such, we are challenging the normative (or cultural) framework of reward in our society. However, we also explained that these conventions are internal factors and can be changed, so that, in our modern current societies, we strive to do better than just endure the asymmetry of information where success is observed while skill and merits are hidden. In the next section, we will suggest how this can be done.

4. Challenging the normative framework of reward

4.1 The three cases: (i) outcome based reward; (ii) risk-adjusted outcome based reward and (iii) prospective reward

Based on our previous observations, we carve out three complementary cases, each with specific conditions that require a particular reward model.

4.1.1 Outcome based reward

In the first case, a process is evaluated based on a snapshot view in the present. This is the typical situation of assuming success from one single, path-independent, observation. It is closely related to Dietrich Dorner’s observation of people acting ‘ballistically’ (Dorner et al.
1990), without self-reflection, deluded in having solved problems merely by means of one single action, without any need to look back and check for the consequences and the effectiveness of the action. This first case is our base case for rewarding success. We will refer to this as the ‘outcome based’ case or reward, it will be studied in detail in section 4.2.

4.1.2 Risk-adjusted outcome based reward

In the second case, a process is evaluated by carefully analyzing the past and the present. How was the current success obtained? As explained in the previous section, this approach is acceptable for processes under quasi-stable environmental conditions, where a proper historical assessment can be done, and results can be described statistically. As such, the inductive scientific method can be applied. This second case can be seen as an extension of the first; reward is not a function of one single observation of success, but is based on success corrected for risk, where risk is a quantitative assessment of the historical process. The second case is a first example of rewarding process and skill, this is done by correcting success for risk. We will refer to this as the ‘risk-adjusted outcome based reward’ case, it will be discussed in section 4.3.

4.1.3 Prospective reward

The final case represents a process in a changing environment. Here, history is not representative for the future but is a resource from which selective information can be extracted to anticipate future scenarios. The process is evaluated by assessing the past, the present and the future. The reward model cannot solely rely on a statistical analysis of past observations but should be based on the capacity to learn and adapt and ‘navigate the future’. Here, the deductive scientific method is applied. This third case is an extension of the second case, but the risk assessment is extended beyond the statistical analysis of the past. This is our second example of rewarding process and skill. We will refer to this as the ‘prospective reward’ case, it will be discussed in section 4.4.

4.2 Outcome based reward

4.2.1 Characteristic time needed to assess skill from success

While studying scientific output in research laboratories, the 1956 Nobel Prize winner in Physics, William Shockley, found very large spreads in productivity, with deviations up to a factor of one hundred between extreme individuals. This result was quite surprising as most rates of human activities vary over much narrower limits (Shockley, 1957). Physiological parameters such as heart rates, physical activities like running or intellectual performance such as school results do not show a variability greater than a factor of 1.5 to 2.5. The basis of the explanation, according to Shockley, is that large changes in rate of production may be explained in terms of much smaller changes in certain attributes. Suppose that an agent wants to finish a certain task in a given period of time, and that an outcome results from the combination of n factors (or sub-tasks) $F_1$, $F_2$, ..., $F_n$. Quantitatively, the probability of completing this task can be approximated by the product of these factors. Then, the productivity (P) of this agent can be given by the following formula:

$$P \approx F_1 F_2 F_3 \ldots F_n$$  \hspace{1cm} (1)

Thus, if one individual exceeds another by 50% in each of 10 sub-tasks, his final productivity will be larger by a factor close to 58. According to Shockley’s model, small variations in factors will aggregate up to much larger variations in success in broader activities.
On the basis of statistical studies of the rates of publications in research laboratories, Shockley found out that not simply the rates of observations, but its logarithm had a normal distribution. The existence of this ‘log-normal distribution’ naturally follows from equation (1): the logarithm of the product is the sum of the logarithms of the different factors. If the factors are independent, then to a good approximation, and if the central limit theorem is applicable, their sum will be normally distributed and so will be the logarithm of the productivity (Shockley, 1957).

Let us pick up from here and return to the finding that a certain agent uses a combination of skill and luck when completing an activity or playing a game. Building further on Shockley’s insights, the distribution of the outcome of this task, at a certain point in time, would be log-normal. In that case, its time dependent evolution can be represented as a stochastic process such as a Geometric Brownian Motion (GBM):

\[
\frac{dS_t}{S_t} = \mu \, dt + \sigma \, dW_t
\]  
(2)

where the percentage change \(\frac{dS_t}{S_t}\) in outcome of success, in an infinitesimal time-step \(dt\), is fully characterized by the percentage drift, \(\mu\), which represents the skill part, and the percentage volatility \(\sigma\), which in our discourse embodies the luck component. The stochasticity is introduced by \(dW_t\), which is the increment of a Wiener process, also known more prosaically as Brownian Motion.

Following a GBM, the excursion after a time \(T\) is typically:

\[
\ln [S_T] \sim (\mu - \frac{\sigma^2}{2}) T + x_i \sigma \sqrt{T}
\]  
(3)

where \(x_i\) is a random variable of zero mean and unit variance. The first term \((\mu - \frac{\sigma^2}{2}) T\) in the r.h.s. of (3) is the cumulative effect of the skill component and the second term \(x_i \sigma \sqrt{T}\) is the luck part. The term \((- \frac{\sigma^2}{2} T\) in the skill component is the result of multiplicative noise in the stochastic process. For most applications, this correction term is small, so for the simplicity of the argument, let us assume this term to be zero.

There is a characteristic time \(T^*\) at which skill and luck will contribute equally to the outcome of the GBM process. At that time \(T^*\):

\[
\mu T^* = \sigma \sqrt{T^*}
\]  
(4)

yielding:

\[
T^* = \left( \frac{\sigma}{\mu} \right)^2
\]  
(5)

For times \(T\) smaller than \(T^*\), the luck component dominates, and the process is diffusive or random; when the outcome of the process is evaluated at times \(T\) larger than \(T^*\), the skill component dominates, and the process is drifting.

This brings us to our first conclusion:

*When evaluating a drift process unconditionally, based on one single observation, one has to use time as the divider between skill and luck. Only when time exceed significantly the characteristic time, as expressed in equation (5), will the outcome of the process, the success, be a good indicator for skill. For shorter timeframes, luck will dominate and the success by itself is not a good indicator for skill.*

The characteristic time differentiates between the concepts of Minyi and Minxin, which were first put forward by Mencius, an eminent Confucian philosopher who lived from 372 until 289
BCE. The first term refers to policies based on short-term thinking, which can change overnight based on the public opinion, the second tends to be stable and lasting, reflecting long-term interest and a holistic point of view (Weiwei 2017).

4.2.2 Time as a divider

We argue that conventions in our society reward short term individual success irrespective of the long-term fitness of the system. These conventions are internal factors. They have a strong impact on the reward process, but they can be changed by the agents. In any equitable process, the most successful agents should also be the most skilful. If a process, as defined in figure 2, uses a strategy that understands the contribution of skill and luck in success, this will result in a fair use of resources and a higher fitness of the system. When we only have a snapshot view in the present, in what we defined as the ‘outcome based’ case, time will be the most import factor that differentiates skill from luck. A rule-of-thumb that can be used in this is the characteristic time.

To go beyond this simple heuristic, let us build a model based on a heterogenous population of N agents. They participate in an activity, the outcome of which follows a GBM process. Each agent has an individual share of skill $\mu_i$ and risk taking $\sigma_i$. After a time-step $\Delta T$, the agent’s realized success can be calculated from equation (3): the skill part is equal to $(\mu_i - \frac{\sigma_i^2}{2}) \Delta T$, and the luck part is proportional to $\sigma_i \sqrt{\Delta T}$. After the agents have played, we split the population up in deciles, each containing N/10 agents, according to their realized individual success after the time-step $\Delta T$, and not using the “real” $\mu_i$ and $\sigma_i$ values that were initially given to each of the agents, and which are assumed not directly observable. We calculate the average of the skill $\mu_i$ and the luck $\sigma_i$ for each decile. The purpose of this simulation is to see under what conditions it is possible to separate “real” skill from “real” luck, based on one single observation of success, and thus to simulate when outcome based reward can be used effectively. The simulation is repeated for different $\Delta T$, which we will call the “vetting period”, the time needed to assess the qualities of, or to “vet” the agent. The methodology is explained in full in section A.1 of the Appendix, and the results are presented in figure A.1, for four different populations with increasing heterogeneity.

The results of the simulation show clearly that there are two different ways to segregate skill and luck: either one can select and reward lucky agents hoping to catch some skilful agents, or one can avoid or punish lucky individuals.

The first approach is rather trivial. The top deciles, with the most successful achievers, contain the most lucky (and also some of the skilful) individuals, this can be clearly seen in the four uppermost subplots in figure A.1. This is the classical strategy of rewarding success, irrespective of the relative contribution of luck in the outcome. In line with our calculations of the characteristic time in the previous section, this strategy, however, is strongly dependent on the heterogeneity of the population and is very sensitive to the length of the vetting period. The longer the ‘vetting period’ is with respect to the characteristic time, the better one can select highly skilled individuals from the population, based on a single observation of success. We will refer to this strategy as the reward-success strategy.

Interestingly, however, when one turns the problem around, by deselecting luck, instead of selecting success, a second strategy reveals itself, which is only weakly dependent on the heterogeneity of the population and the vetting time. This can be clearly seen in the four middle subplots in figure A.1. By taking the middle deciles, thus avoiding the top and bottom deciles, we select a subpopulation of agents with a much lower relative contribution of luck. This is
much less intuitive, as it rewards (or selects) agents which are only moderately successful and explicitly ignores the most successful and the most unsuccessful. We will refer to this strategy as the punish-luck strategy. Pluchino et al. (2018) recently published the results from an agent based model, where they come to the similar conclusion that the most successful agents are almost never the most talented ones.

Both strategies are not aligned, either one selects the agents in the top deciles to reward success, or one avoids the top and bottom achievers to punish randomness (either lucky or unlucky outcomes). Which one should it be? Obviously, and, almost trivially, when there is plenty of time to assess the agents’ performance, one should just sit and watch and select those agents who surface into the top deciles. However, how does one know if one has waited long enough and that the observed success is not just a series of lucky streaks? Or, what to do in case of very heterogeneous populations or only relatively short time availability as is often the case in practice? To put things in perspective, for the problem of selecting financial investments, given that typically $\mu \sim 5\% - 10\%$ and $\sigma \sim 20\% - 30\%$ per year, the characteristic time $T^*$ given by expression (5) is between 4 and 36 years. This means that, using the (unconditional) reward-success approach, it is almost infeasible to assess the value of an investment if the holding period is not longer than 4 years, a very long period indeed for most investors. As a corollary, this illustrates the well-known fact that most superior performing financial funds enjoy significant luck, while the truly skilled ones are only a tiny fraction (Barras et al., 2010).

To answer these questions, we must not look at skill or luck individually, but at skill corrected for luck, as in the well-known Sharpe ratio used in finance, defined as the ratio of skill divided by luck $(\mu/\sigma)$. Figure 3 is based on the simulation, as explained before, but this time, the results are represented differently, with the x-axis, in log-scale, showing the vetting period and the y-axis showing the Sharpe ratio. The results for the different deciles are represented by curves with different colors. The horizontal black dotted line gives the Sharpe ratio for a one year out-of-sample period for the population and the black barred line gives the optimal allocation, which is defined as the winning decile for each vetting period. It is striking that, for shorter vetting periods, say less than one year in the results below, the Sharpe ratio of the optimal allocation is almost flat. Then there is a shift from an allocation to the median deciles to an allocation to the first decile, which shows in a step-like profile for the optimal allocation function.

It is interesting to discuss the results for the four different populations:

- For population 1, in the upper left subplot, the punish-luck strategy is dominant for vetting periods up to one year. This can be seen from the fact that the deciles 3-5 are optimal for those vetting periods. After that, the reward-success strategy wins. The transition period between both strategies is around the characteristic time, which agrees with $(\mu_{\text{luck}}/\mu_{\text{skill}})^2$, that is one year;
- For population 2, in the upper right subplot, the punish-luck strategy is dominant for vetting periods up to four years. After that, the reward-success strategy wins. The transition period between both strategies is around the characteristic time, which agrees with $(\mu_{\text{luck}}/\mu_{\text{skill}})^2$, that is four years;
- For population 3, in the lower left subplot, the punish-luck strategy is dominant for vetting periods up to one quarter. After one year, the reward-success strategy wins. The transition period between both strategies is around the characteristic time, which agrees with $(\mu_{\text{luck}}/\mu_{\text{skill}})^2$, that is one year;
- For population 4, in the lower right subplot, the punish-luck strategy is dominant for vetting periods up to one year. After that, the reward-success strategy wins. The transition period between both strategies is around the characteristic time, which agrees with $(\mu_{\text{luck}}/\mu_{\text{skill}})^2$, that is four years.
Fig. 3: Sharpe ratio (y-axis) as a function of the vetting period (x-axis, log-scale) for the different deciles. Each subplot represents a different population whose distribution of individual skills and lucks are log-normally distributed with parameters given in the insets of the panels (see Appendix A1).

In his ‘Logic of Failure’, Dietrich Dorner (1990) explains that people act ballistically, without self-reflective examination. Most often, success is evaluated unconditionally, by looking at one single snapshot observation of the present, disregarding any of the underlying processes. For such an approach, the lessons from our simulations are clear. Only if one has the luxury of very long vetting periods, can one appraise skill from success in this way. For most real human activities, the distributions of skill and luck, together with the urgency of decisions, requires avoiding the ‘Illusion of Success’ that tends to blind us and to misguide in the search of true skill and thus persistence of success. Indeed, one should consider extreme success suspiciously, more as the evidence of lucky winning streaks rather than revealing genuine quality. In fact, reasonable levels of success (the middle deciles) are much more likely to be true signals of persisting performance.
4.3 Risk-adjusted outcome based reward

Up to now, we have focused on single observations. But sometimes, we are able to include intermediate results in our evaluation process. If the underlying processes are quasi-stable, the past is a good indicator for the future and a risk-adjusted outcome based reward model is acceptable. More concretely, this means that we can correct success for risk, and adjust the outcome for the path that has been followed by the agent to get to that success.

How does such a risk-adjusted outcome based evaluation differ from the outcome based model that we introduced in the previous section? To answer this question, we modify the simulation. Again, we sample N agents, and we let each of them act over a period $\Delta T$ following the same GBM process. However, now we record intermediate results. These allow us to estimate the realized volatility of each agent, which will be seen here as a simple proxy for their risk.

Instead of using the direct outcome, after a time-step $\Delta T$, of this process, as a simple measure of success, this time we divide this outcome by the estimated realized volatility to come to a Sharpe ratio for each agent. This ratio is used to rank the agents and sort them in deciles, each containing N/10 individuals. For each of the deciles, we calculate the average skill and luck from the ‘real’ values of each of the agents. For our simulation, we use a vetting period of one year, and we gradually increase the number of intermediary observations from 2, 4, 8 … to 256. The results are shown in Appendix A.2.

The results are quite clear, even for a very crude statistic using only two observations: the Sharpe ratio selects higher skill and lower luck agents, monotonously over the 10 deciles. By adding one single intermediate step, which allows for a very crude estimate of the volatility based on two observations, the typical smile-shape for luck, which was seen in our first case, completely disappears.

By changing our definition of success from a single observation to an evaluation of the process, the asymmetric impact of luck (in the shape of a smile) that we saw in the outcome based model completely disappears. For quasi-stable processes, ‘rewarding the process instead of success’ is already quite successful for very crude estimates of this process using only a few intermediate observations (assuming that the measurements are reliable and faithful).

4.4 Prospective reward

In the first case, we decided to simply reward success and select, or favor, those agents which had the best outcome from an activity or a game, without looking at the process that led to this result. We simulated this to find out that, following this approach, only time can separate agents with different qualities. If $\Delta T$ in our simulation is below the characteristic time, we can avoid selecting agents that were mostly lucky; if it is above, we can select agents that have high skills based on their success.

In the second case, we introduced retrospective observations. This allowed us to make a risk assessment of the process and to select or favor those agents who had the optimal risk-adjusted result from an activity or a game. By correcting for the path followed by the agent, this approach rewards the process. The selection criterion improved significantly, even for a very crude estimation of risk based on one single intermediate observation.
Our third and final case takes place in a changing environment. History is no longer representative for the future but is a resource from which selective information can be extracted to anticipate future scenarios. To study this ‘Prospective reward’ case, we have to leave our simulation behind and follow a deductive scientific method. Time, nor historical estimation of risk, will be of help to differentiate agents. Now, we have to introduce a qualitative methodology.

4.4.1 Navigating into the future as a complex adaptive system

‘Navigating into the future’ has been the research subject of Philip Tetlock, his wife Barbara Mellers and collaborators for more than 30 years. Back in 1984, they started organizing forecasting tournaments to identify the distinctive features of good quality expert judgements and predictions. In their Good Judgement Project, several thousand people act as volunteer forecasters. These projects serve a dual goal: on the one hand, they provide a real-life laboratory to study the act of forecasting; and on the other hand, they harness the wisdom of the crowd and create an optimized ‘forecasting machine’. The central theme in their study is to be able to separate skill from luck in prediction. The recent book (Tetlock and Gardner, 2015) contains powerful recommendations and guidelines to set up our ‘Prospective reward’ case.

In our ‘Prospective reward’ case, we want to incentivize skillful navigation into the future. Navigation needs an operating system. Generally speaking, there are three different types, each with a higher degree of “intelligence” (Gell-Mann, 1994). The first one is direct adaptation. That is like a thermostat, which simply reacts when a certain threshold is crossed: “too cold”, “too hot”, “too cold” … This most basic management system corresponds to our ‘outcome based’ case. A more intelligent approach follows an expert system, which is a static internal model, like a decision tree, based on historical expert experience: “if …, then …, else …”. The emphasis here is on control, and the belief that systems can be controlled with sufficient knowledge of historical input-output relationships. This corresponds to our Risk-adjusted outcome based reward case. Finally, the most intelligent operating system is a complex adaptive system, which is an expert system that can learn from a changing environment by a process of mutation and selection, like in biological evolution. It has a set of built in rules (scheme, gene, meme). There are fitness criteria that allow for selection, bad schemes become obsolete. Additionally, there is variation through reproduction and mutation. Selection and variation are the basic ingredients that allow for the system to learn and adapt dynamically to its changing environment.

To manage the ‘Prospective reward case’, we introduce a complex adaptive system that consists of five different principles: ‘Observe’, ‘Decide’, ‘Execute’, ‘Challenge’ and ‘Explore. There is a large body of academic research on each of those topics. In the following, we will discuss the insights that are most relevant based upon the work of Tetlock and Gardner (2015) and Kahneman (2011). For more information, we refer the interested reader to those resources and references therein.

Observe

Any observation starts with a good understanding of the impact of luck versus the effectiveness of skill. If the environment is not sufficiently regular to be predictable, or if the available time does not provide sufficient opportunity to learn, any hard work will only pay off via processes that are undistinguishable from chance. In this context, it is particularly important to separate epistemic from aleatoric uncertainty. The former is something you don’t know yet but, at least in theory, is knowable, like an engineer opening a mystery machine to find out its workings and
be able to predict its behavior. The latter is uncertainty of the type that is unknowable. In its simplest form, this means separating the signal from the noise.

By construction, the environmental conditions of our third case of ‘Prospective reward’ are not stable, and predictability is poor. In these circumstances, it is very important to be consistent, which means that one has to neutralize unnoticed stimuli as these may impact our observations through priming, anchoring or framing. This can be done by complementing as well as challenging a personal model of the world, from which a subjective inside view condenses, with objective outside information, or benchmarks. In this process, one has to challenge the internalization of observations with rules of thumb. These are also known as simple back-of-the-envelope calculations based on common sense that help the observer to construct a sanity check, or as famously stated by Robert Solow (2010), to make a “smell test”. A very simple, but often neglected, technique is the use of independent base rates. For example, when studying an investment opportunity in a start-up, a venture capitalist should start from an independent assessment of the survival rate of comparable companies at a similar stage, and then use this as an anchor to be adjusted using the particular, specific inside information.

**Decide**

In his book, Victims of Groupthink, the psychologist Irving Janis (1972) explains how group dynamics have a very strong impact on the quality of decisions. He uses the Kennedy administration as an example, and more particularly zooms in on the differences in handling the Bay of Pigs invasion versus the Cuban missile crisis.

An inquiry, initiated after the Bay of Pigs fiasco, brought up that the Kennedy administration had a flawed decision-making process based on cozy unanimity. As a consequence, independence of thought and judgement was lost, and individual decision makers advocated superficial analyses or even endorsed plain errors. The group dynamic did not cancel out mistakes, what would result in a ‘wisdom of the crowd’ effect (Surowiecki, 2004), but accepted and piled up bad judgment, what lead to a ‘collective folly’ (Tuchman, 1984). Drastic changes in the decision-making process of the Kennedy administration were implemented. Skepticism was the new watchword. One could only speak as specialist in one’s own area of expertise but was allowed to challenge any expert as a generalist. On many occasions, new advisors were brought in to bring new perspectives. JFK himself would often leave the room to let the group discuss more freely and to avoid biasing the group opinion by his personal clout. This new approach paid off with the successful handling of the Cuban missile crisis. Opposed to what is often advocated, a group should not strive for consensus, to the contrary, consensus should be seen as a warning flag that groupthink has taken hold.

Tetlock and his fellow researchers come to the following conclusion of how a good decision is made in a group. First, the diversity of knowledge and opinion should be optimized. They call this applying ‘the dragonfly view’; any observation should be multi-faceted. Any similarities but also differences between these different viewpoints should be carefully explored and dissected. It should be avoided to put too much weight to the opinion of those who speak early and assertively, causing others to line up behind them (Kahneman, 2011). In summary, as Andy Grove, the former CEO of Intel put it, ‘constructive confrontation’ should be practiced. This recommendation is echoed and strengthened by Ray Dalio (2017), with his “radical transparency” principle: “In order to be successful, we have to have independent thinkers - so independent that they’ll bet against the consensus”.

**Execute**

Once a complex and dynamical ‘game’ is assessed and a strategy is decided, the next step is execution. Von Moltke, the famous 19th century Prussian military strategist, is often quoted as
saying, ‘In combat, no plan survives contact with the enemy’. Mike Tyson, the former American heavyweight boxing champion came to a similar conclusion in his own profession: ‘Everybody has a plan, until they get hit’. Any strategy, that is executed in a dynamical environment, must be constantly re-assessed and adapted following a qualitative approach of observation and decision, as discussed above. But how do we strike the right balance between analysis paralysis and overconfidence?

Learning requires doing, and doing requires execution. This is what Tetlock and Gardner (2015) call, ‘mastering the error-balancing bicycle’. German military history can teach us a lot in this respect, more specifically, the principle of Auftragstaktik. The basic principle of this German mission-type style was that ‘War cannot be conducted from the ivory tower’. This means that tactical decisions should be made locally, optimized on the spot, guaranteeing frequent and rapid decisions, according to estimates of local conditions. However, these local tactics must be aligned with the global strategy. Therefore, every local decision maker must have a clear understanding of the global strategy with orders from high-command that are short and simple with clearly defined goals, that leave all initiative with local leadership: “this is what needs to be done”, “For the following reason”, “I don’t care how you do it”. This approach guarantees an alignment of tactical adaptivity with strategic tenacity and global coherence.

**Challenge**

A basic feature of learning systems is that they begin with a bias; the future is anticipated in a number of scenarios with different expected probabilities. This is the starting point of a feedforward mechanism: the expectation is checked against an observation, the discrepancy is analyzed, which leads to an adapted model of reality and a new bias with updated expected probabilities (Seligman et al. 2013, 2016). The central feature of this mechanism that closes the feedback loop, which makes learning possible, is continuous monitoring to identify existing biases and then challenging them.

In the context of decision making and forecasting, Tetlock and Gardner (2015) put it as follows: *Don’t try to justify or excuse your failures. Own them! Conduct unflinching postmortems: Where exactly did I go wrong? ... Also don’t forget to do postmortems on your successes too. Not all successes imply that your reasoning was right. You may have just lucked out by making offsetting errors. And if you keep confidently reasoning along the same lines, you are setting yourself up for a nasty surprise.*

Challenging, by conducting postmortems on failures and falsifying successes, makes the system adapt. Like in ‘Execute’, also here, a delicate balance should be found in ‘Challenge’. A concrete application is to learn not-to-control or to-control-less and let the system adapt, under gentle nudges at right rare times. Examples include helping the immune system to cure a patient rather than the all-control approach of standard medicine that often tries to substitute by killing the microbes, with the collateral damage of wiping out a part of the immune cells and microbiome. Another example is the Iraq and Libya invasions by the US, which suffered arguably from a case of over-control syndrome and over-confidence, thinking that they could bring democracy and peace. In contrast, the Ottoman and the British empires at their peaks knew how to let a lot of autonomy and to nudge towards balances of power between the many co-existing communities (Hellerstein, 2016). Sometimes, the best intervention is the act of deliberately doing nothing, following Hippocrates’ ‘Primum non nocere’, first do no harm.
Explore

‘Observe’, ‘Decide’, ‘Execute’ and ‘Challenge’, are the necessary ingredients for a self-learning and adaptive system. However, it is still possible that this optimizes ‘in a niche’, based on local conditions. Any system should be seen as a global optimization problem, the more so in an ever-changing environment. To avoid being trapped in local optima and frozen in the presence of changing circumstances with uncertainty, we need to explore, go beyond the ground paths and we need to play.

In their book, ‘Why Greatness Cannot Be Planned’, Stanley and Lehman (2015) explain that, only by doing activities that fulfill our curiosity without any pre-defined objectives, true creativity can be unleashed. They call this the ‘Myth of the Objective’: Objectives are well and good when they are sufficiently modest … In fact, objectives actually become obstacles towards more exciting achievements, like those involving discovery, creativity, invention, or innovation—or even achieving true happiness… the truest path to “blue sky” discovery or to fulfill boundless ambition, is to have no objective at all.

According to Ohid Yaqub (2018), the pursuit of efficiency and a mechanical reduction of errors in scientific research may suppress the error-borne mechanism of serendipity. Based on the Merton archives, he could collect hundreds of examples of serendipity in research, discoveries based on simple happy accidents or sloppiness when something has inadvertently been dropped, spilled, heated, exploded, forgotten about in pockets or drawers or laid to rest over holidays, contaminated or subjected to methodological blunders and/or equipment malfunction.

4.4.2 Dividing the dollar

In this paper, we premise that reward in our society is myopically focused on success and that the role of chance is not properly discounted. For the outcome based case, we proposed a strategy dependent on the characteristic time and, for the risk-adjusted reward case, we proposed a strategy based on a historical assessment. Both cases are quantifiable as they look at historical realizations of a process.

The prospective reward case takes a completely different perspective. Here, we should incentivize systems or agents according to their ability to ‘navigate the future’. This requires a qualitative assessment that is difficult to fit into objective top-down directed criteria. How can a reward mechanism guarantee successful self-organization growing from the bottom up that ensures rewarding skill and not luck? This question arises when hiring, when "scouting" prospects for professional sports, when choosing a mate, and so on.

A possible step is to start by recognizing that the observe-decide-execute-challenge-explore framework, and most of our activities, involve groups of people, collaborators, team players… All the steps from process to success and then to reward are in the end the result of the aggregation of individual efforts contributing to the whole. Until now, we have focused on the problem of identifying the sources of success, as if sharing out reward was a simple act. In fact, the way the recompense is allocated also constitutes a crucial component to success (while it leads to conflicts and to disincentives if badly implemented). But identifying the true contribution of each member to the group is devilishly difficult, especially when members have different complementary domains of expertise and in the presence of unpredictability. Who has not been part of a project, where the sum of the self-attributed contributions over all members of the team was much above 100%? Even stringent quantitative criteria may be difficult to align
with personal subjective perceptions and, often, do not apply in many situations with “soft” qualitative dimensions.

In their work titled ‘Dividing the dollar’, de Clippel et al. (2008), followed by Tideman and Plassman (2008) in a paper called ‘Paying the partners’, provide a general and powerful methodology to divide profits in a partnership of three or more individuals in the absence of rigorous quantitative criteria. The principles behind the distribution mechanism are the following. First of all, the system should be impartial, meaning that no partner is able to affect his own share by the input he provides. Next, it should be ‘objective’, so that a partner only gives input about the others’ performance and that his self-evaluation cannot affect the share of any other partner. Finally, it should be ‘consensual’, the division of shares should be consistent with all the input that the partners provide. It turns out that, for three partners, there is a unique formula that obeys to the three requirements and, for more partners, there is a family of “optimal” division rules that are consensual, strategy-proof (no need of bargaining), and objective. Operationally, this methodology is very practical and intuitive as each partner has to provide the input to calculate the ratio of the shares of each pair of his or her colleagues. How much more should partner i receive than partner j? A mathematical model aggregates the cash pool to all the partners.

Such a framework, if applied operationally, would go a long way in incentivising team members to prioritize efforts and skill, rather than counting on signalling, bargaining and strategies to get rewards.

5. The reward hierarchy

5.1 Overview

Let us now bring the different cases, outcome based reward, risk-adjusted outcome based reward and prospective reward together in a single hierarchical framework. The mind-map in figure 4 gives a comprehensive overview:

- When the environmental conditions are strongly stationarity, then, one-single, unconditional, path-independent observation of success can be used as the basis for reward, only if time is used knowingly as a differentiator. If the life of the process is shorter than its characteristic time, then agents with median success should be rewarded at the expense of the extremes with very high or low successes. If the period is longer, then success itself is a good proxy for skill and should be rewarded accordingly.

- In case the environmental conditions show only weak stationarity, we need data to quantify, retrospectively, the path dependency of the success. This means that we normalize success using an adequate risk measure. Incentivization should be aligned with the ratio of success and risk (the Sharpe ratio).

- When there is no stationarity, the management system should be prospective, navigating into the future. This should be based on heuristics that are aligned with our observe-decide-execute-challenge-explore cycle and the reward should be a bottom up system that is strategy proof, objective and consensual
Fig. 4: The reward hierarchy: Three complementary branches representing fundamentally different approaches towards reward. In case of strong stationarity, (life-)time should be used, for weak stationarity, this should be data and when there is no stationarity, one should apply heuristics.

5.2 Tools and systems in the literature

The classification in outcome based reward, risk-adjusted outcome based reward and prospective reward viewpoints is applicable in a broad range of discipline like statistics, game theory, system engineering, psychology, economics, finance, military, political and business strategy... Figure 5 gives a graphical overview, more details and references are given in Appendix A.3.

The graph uses a color code that is based on our assessment. Disciplines colored green are well-adapted to the environmental conditions. Good examples are De Mesquita’s Predictioneer’s game (2009), Sornette’s Dragon Kings (2012), Tetlock’s Superforecasters (2015) or Seligman et al.’s Homo Prospectus (2013, 2016). The red-colored examples do not account sufficiently for the absence of stationarity in the environment. A controversial example is the Capital Asset Pricing Model. In theory, the CAPM includes all the future expectations of all agents, all of whom are supposed to optimize their portfolio and thus converge to the same ‘tangent portfolio’, which becomes the market portfolio. In this sense, it can be seen as prospective. In practice, it assumes equilibrium in a stationarity world. That is why we classify it as a risk-adjusted outcome based approach, i.e. retrospective, because it extrapolates that the statistical properties of the future will be like the past. Other examples are the Martingale
Measure, which describes a process where the most probably observation of tomorrow is the realization of today, Black and Scholes' replicating portfolio methodology (Black and Scholes, 1973) and the technical flaw of overfitting, where correlations are found in data that do not imply causation. Up-and-down economics (Krugman, 1990) is a standard practice in journalism where adaptive, non-stationary, complex systems like the economy or the financial markets are naively reported as ‘went up’ or ‘went down’, with insufficient concern for their prospective nature.

![Diagram](image_url)

**Fig. 5:** A multi-disciplinary view of tools and systems from the literature classified according to viewpoint. The green-colored are fully aligned with the environment, the red-colored do not take insufficient stationarity into account, the grey-colored are just tools. More information and references are given in Appendix A.3.

6. Discussion and applications

We have proposed a hierarchical reward framework that depends on the stationarity, and its lack thereof, of the environmental conditions. When there is strong stationarity, reward can be based on an unconditional observation of success with time as a differentiator between strategies. When there is weak stationarity, data, in the form of historical observations, is key and reward should be based on the risk-adjusted success. In absence of any stationarity, heuristics play the most important role and management systems should be rewarded accordingly. We now examine applications in different fields.
6.1 Finance

Implementing some of our above suggestions could help close the gap in compensation between the financial industry and the real economy e.g. between investment professionals or traders and engineers at the same level of competence and responsibility. This is called the Finance Wage Premium, which leads to a brain drain into the financial sector at the expense of other sectors. In a recent study of Böhm et al. (2018), no evidence was found that more talent, higher productivity or longer working hours, neither on average, nor at the top, could possibly explain this income gap. A more plausible explanation is that financial professionals benefit from an exorbitant rent, associated with their specific position in the flow of money as well as the focus on short-term success rather than true skill and true added value. The reward system in the financial industry should be managed in the prospective domain, while currently it is treated incorrectly in the risk-adjusted outcome based domain, leading to large bonuses when luck plays out and no claw back when losses occur (gains are private, and losses are socialized, or absorbed by the organization).

In that same respect, we showed that risk management, based on historical data, is a tool that can only be used in the risk-adjusted outcome based domain. Nevertheless, financial institutions and regulators allocate almost all their resources to this approach, while ignoring the non-stationarity of the complex financial system and the fact that this should be managed prospectively using heuristics in an observe-decide-execute-challenge-explore cycle. In a speech at Jackson Hole, chief economist and Executive Director at the Bank of England, Andy Haldane (2012) compares this with a dog catching a frisbee. Without having a Doctorate in Physics, a dog is perfectly capable to catch a frisbee. As you do not fight fire with fire, you do not fight complexity with complexity. Because complexity generates uncertainty, not risk, it requires a regulatory response grounded in simplicity, not complexity. More (including gender) diversity in the financial markets, a full understanding of chance in success and a better alignment of incentives, could have a stronger impact on stability than the implementation of super-expensive, enterprise-wide, risk management systems based on historical data, creating a comfortable illusion of control based on assumptions of stationarity.

6.2 Tax policy

Taxation is essential for funding public good and government services but also discourages efforts because the activity that is taxed becomes relatively less desirable: for instance, taxes on wages reduce the incentive to work. There is a large body of theory to determine optimal taxation schemes, such that some social welfare function is maximised subjected to economic constraints (Mankiw et al., 2009).

Consider the situation where tax payers only differ in their ability, i.e. how much they can produce and contribute for a given amount of effort, say time, and the social planner (say, the government) can only observe income but not their ability or efforts (which is quite realistic). Then, economic theory based on the asymmetric information framework advises that the top earners should have the lowest marginal tax rates (Mirrlees and Diamond, 1971). Thus, when skill dominates and luck is absent or small, taxation should be “regressive” to encourage work efforts and improve global welfare.

In reality, as we have documented above, income is often influenced quite significantly by luck or misfortune. If the process could be identified and monitored, and success and income could become strongly correlated with skill and process, as we have argued, the above optimal ‘regressive taxation’ may remain valid. But, there are many situations in which this is not (yet) possible, for a variety of reasons. Then, when success results mostly from luck, it becomes
rational and optimal to tax heavily the incomes that result in large part from luck and have not much to do with merit. In this case, a progressive taxation with very high marginal rates may become warranted. Since success is, in this limit, unrelated to skill and efforts, a large tax rate does not really disincentivize work and instead creates a form of social insurance in which the lucky subsidize the unlucky (Varian, 2001). Progressive taxation with high marginal tax rates becomes the tool of last resort to recover fairness in a luck-dominated environment, reminiscent of our conclusions for outcome based cases where middle deciles are a better forecast of real skill than the best achievers (see figure 3).

From the point of view of a single person, inheritance falls in this luck-dominated regime: some of us are born in rich families and most are not, as if by the throw of a dice of demographics and genetics. This logic would thus support a strong taxation of inheritance, which would have arguably the least distorting effects as they arguably dissuade less to work or to invest than income taxes. However, the situation is not so simple, as reflected by the often-visceral reactions to inheritance taxes. Indeed, the bequeather often thinks of her beneficiaries as a continuation of herself. Thus, considering the heirs as individuals separated from their parents omits the deep ingrained genetics and psychology of human evolution². If one considers a family as a group rather than as a set of individuals, the ‘taxing luck’ argument for inheritance weakens.

In general, skill and luck both contribute to success, but to different degrees in distinct activities (see figure 1). This suggests improved progressive taxation designs, where the marginal tax rates could be adjusted to the level of skill-versus-luck involved in creating value and success in each professional activity. In other words, taxation would act here as a correction mechanism in a market that fails to correctly associate reward to skills and efforts. With such a design, soccer super-stars should be taxed more than basketball super-stars... and financial professionals, who are benefiting from much more luck, would be taxed at a higher marginal rate than, say, engineers in the industry sector with similar skills.

6.3 Politics

In democracies, politicians get access to positions of power via the votes casted by a large electorate. However, this democratic process often exhibits significant random and biasing components (Galam, 2012). Many recent examples suggest a strong random unpredictable component, in addition to vulnerability to social engineering and interest group targeting. For instance, in Gore vs Bush (2000 US presidential election), the winning candidate lost the popular vote, and this election is considered one of the closest elections in US history in which Bush won the decisive state of Florida by a margin of just 0.009%, or 537 votes. If a genuine ‘reward process’ was implemented to the political dynamics (other than that of being re-elected, which leads to tactical positioning), politicians would become accountable for their promise. This calls for new designs as discussed below.

An issue of widespread concern is ‘democratic backsliding’ and the current rise of so-called populism (The Economist Intelligence Unit, 2017). Among the proposed explanations, consider the progressive impoverishment of the bottom 90% of the population in Western countries since the responses to the 2008 financial crisis in the US and the 2010 sovereign debt crisis in Europe in the form of bank bailout programs, quantitative easing and low interest policies. As a result of these policies, stock and real-estate markets have boomed while wages have

² “The selfish gene” book by Richard Dawkins (2016) makes this point particularly forcefully, by taking a gene-centric view of evolution, in which individuals of an ancestry-descendent genealogy are the connected successive “vehicles” of evolution of gene replicators.
plateaued, leading to an increasing inequality, where the top 1% and even more so the top 0.01% have greatly benefitted, while the bottom 90% have stagnated or lost. In this context of frustration and economic pain, an implicit and sometimes explicit question arises as to whether the elites have special qualities or better skills that justify their wealth increase. Or are they just rent holders benefitting from privileged positions? We suggest that a new reward system, emphasizing process and not just success, imbedded into new ‘cultural conventions’ as discussed in section 3 and figure 2, could bring back more fairness and quench this anger. This relates to the discussion above on optimal taxation, which could go a long way towards re-establishing confidence in the political process by correcting for market failures.

Besides the response to the call for fairness by the angry masses in the form of the rise of populism, there is also a need for improved democratic processes that reward politicians for their positive long-term contributions to society rather than for their demagogy. As already mentioned, new designs are needed, both at the level of global welfare as well as for promoting more satisfaction on the individual citizen level. There is an active community working on this topic, with the suggestions of a number of improvements such as flexible majority rules, two-stage unanimity rules, rotating agenda setting and agenda repetition in combination with flexible majority rules, minority voting, balanced voting, assessment voting and so on.3 Somewhat similarly to the market approach to select promising scientific proposals discussed below, incentive contracts put into law for politicians and elections (dual democracy) can help improving democratic election processes.4 A complexity science approach also suggests a number of policy recommendations, including entrenching diversity by regulation, monitoring feedbacks, and ensuring connectivity (Wiesner et al., 2019). All these are schemes to improve the democratic process via incentives that align the interest of the different stakeholders, while providing safeguards against exploitation of unfair positions.

6.4 Science

The winner-takes-all mechanism also plays an important role in science, where 'frozen accidents' and 'first mover advantages' create superstars, with large rewards given to few (Nobel prizes, large research grants ...) (Simkin and Roychowdhury, 2018), while the achievements are often a large team’s work and benefit from a supportive social context as well as technological and conceptual maturations (Merton, 1961). There is a culture of social hypes where 'well-dressed trivia' obtain the majority of the attention in top journals with wide circulations (Buchanan, 2009). Indeed, it is a sociological fact that truly innovative discoveries are almost never published in prominent scientific journals and only recognized after much efforts from their authors: the system resists innovations and revolutions (Kuhn, 1970; Dyson, 1988), accepting easily only understandable “marketable” (and thus ‘small’) successes.

The research funding system based on grant proposals and its review system in many countries may be seen as an attempt to take a prospective approach to select the skillful scientists and potential fruitful ideas. However, its implementation is costly and very time consuming for most researchers, with disappointing results favoring incremental rather than revolutionary research, which further entrenches the accepted paradigms. These defense mechanisms make fundamental shifts in our understanding (the paradigm shifts) extremely difficult. A variety of ideas have been proposed to improve this state of affairs by using different

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3 See e.g. http://www.mip.ethz.ch/research/areap/constitutionaldesign.html
4 See e.g. http://www.mip.ethz.ch/research/areap/bindingelectionpromises.html
versions of the wisdom of crowd mechanism, in the presence of significant incentives. For instance, we could imagine a market of proposals that scientists exchange or trade.

In one incarnation, every scientist is endowed with the same equal share of the funding budget annually and then has to donate a fixed fraction to other scientists whose work they find important and promising (Bollen, 2018). This exchange process could be iterated with different percentages at successive rounds, so that scientists receiving more than they need can themselves redistribute.

In another approach, a research proposal would be associated with an option, where the option buyer would have a financial stake in its scientific future and the option would pay off if the project is successful, where the money of the payoff would be coming from the proponents who would similarly benefit if it pans out into a successful development (see Weinstein in Buchanan, 2009). Supporters of gradual increase in science would be option sellers, which would be comparable to a short volatility and long theta trading strategy in finance. As long as scientific progress follows a smooth process, their payoff would be similar to a fixed income investment. On the buy side of the options would be the mavericks. They would be long volatility and short theta. This means that they would be bleeding cash periodically in small amounts, but that they would be payed handsomely if a shock occurs.

Expanding on this idea, a market among scientists could be established in which proposals are going through a virtual IPO (initial public offering) and their shares are traded. Each scientist writing a proposal (analogue to a business plan) receives a fraction of the shares associated with her proposal while the other shares are offered to the community (defined as people who have relevant scientific expertise and are endowed with a virtual budget). The scientists are incentivised to buy them with their endowed virtual money because they estimate that these other proposals have value and will also be highly rated by the community. The research proposals should include both forward science as well as falsification endeavours. Some groups may focus on trying to prove that a theory works, others will do the opposite. If a budget is allocated using this market mechanism, it is in every agent’s interest to be transparent and disclose data, results and analyses, similar to the current financial reporting required of listed companies. The information disclosed by validators of a theory will attract falsifiers, and vice versa. The result will be a dialectical dynamic between validators and falsifiers, both having to convince the scientific community, in a transparent way to be able to secure future funding.

The efficiency of financial markets ensures that the best proposals would be in high demand, pushing their market prices up\(^5\). The real funding received by scientists would then be an increasing function of the value of their final virtual portfolio, equal to the sum of the shares’ value of their proposals and the shares’ value of other proposals that they have acquired. This design fills two needs with one deed\(^6\): it rewards scientists for the quality of their proposals, as judged by their colleagues via the market mechanism, and for their efforts in providing high quality assessments of others’ proposals. Bad investors, who exert poor review judgement,

\(^5\) Here, the term ‘best’ refers to a ranking anointed by the choices of the scientific community. This mechanism does not necessarily avoid the emergence of social hypes and ‘well-dressed trivia’ that could obtain the majority of the attention. But see below the discussion on ‘social bubbles’.

\(^6\) A prototype of this design, called xYotta, has been developed at the chair of Entrepreneurial Risks in ETH Zurich, to provide a radically innovative way of how courses are taught, and group work is organized and evaluated. xYotta utilizes the wisdom of the crowd (the students in a University set-up) and market mechanisms to identify the best projects, ideas and talents. It has been rigorously tested by more than a thousand ETH graduate students in several courses and research projects over several years (Sanadgol and Sornette, 2017; Sornette et al., 2018).
would be penalised. This system would thus not only reward the best proposals but ensure a self-organised selection of high-quality reviewers. This could even make obsolete the publication in peer-reviewed journals.

A concern is that market bubbles may occur due to extreme enthusiasm for a few projects, leading to a concentration of allocations to them. However, such transient excesses may not be bad after all, once one understands that great breakthroughs require 'social bubbles' during which high risks (and investments) are taken beyond the standard conservative cost-benefit analysis (Gisler and Sornette, 2009; 2010; Gisler et al., 2011). This is the opposite to the conclusions on taxations that should cure the market failure to distinguish efforts and skill from luck. In science, one would want to incentivise more risk taking and the maverick ideas and projects. However, scientific discoveries are high volatility events often based on luck and serendipity (Sornette and Zajdenweber, 1999). Taking the point of view of scientific advance and innovation, backed by the principle of social bubbles, leads to promote risk taking to explore. Contrarily, from a tax perspective, we have argued above to disincentivize risk taking, proposing higher taxes for financial professionals than for engineers.

Thus, different activities should be treated differently. On the one hand, scientists should be incentivized strongly to take risks and explore the unknown. A more efficient innovation process that fosters a culture where entrenched paradigms are strongly challenged would increase social welfare. Without falling into technical solutionism (Morozov 2014, Spiekermann 2017), we propose that a good innovation system is our best chance to provide new solutions to the problems that our society is facing7. Such positive risk-taking behaviour could be promoted by introducing a market mechanism in the scientific enterprise. For the financial industry and in politics, however, this should be completely the opposite. There, we propose to introduce a market correction mechanism that rewards people and processes that foster long-term and global social welfare. In short, gambling in science is beneficial for the common good, gambling in politics and finance is harmful.

6.5 The scientific enterprise within the observe-decide-execute-challenge-explore cycle

In summary, the scientific enterprise can be structured using our proposed observe-decide-execute-challenge-explore cycle as follows.

Observe:

- Have special attention to outliers and deviating observations.
- Not only focus on positive results but also on negative results.
- Use statistics correctly.
- Be aware of data snooping.

7 Richard Smalley, a Nobel prize laureate in Chemistry, famously developed a list of humanity’s top ten grand challenges in the 21st Century: (1) energy; (2) water (more than 1B people lack access to safe water); (3) food; (4) environment; (5) poverty (3B people living on less than $2/day); (6) terrorism and war; (7) disease; (8) education; (9) democracy and (10) population (could double in the 21st Century ~ 6.4B people in 2004 and ~ 7.7B people at the end of 2018). See (Smalley, 2005).

It is interesting to compare with the UN Secretary-General’s High-level Panel Report on Threats, Challenges and Change, which identified ten threats for the World: (I) Poverty; (II) Infectious disease; (III) Environmental degradation; (IV) Inter-state war; (V) Civil war; (VI) Genocide; (VII) Other atrocities (e.g., trade in women and children for sexual slavery, or kidnapping for body parts); (VIII) Weapons of mass destruction (nuclear proliferation, chemical weapon proliferation, biological weapon proliferation); (IX) Terrorism and (X) Transnational organized crime. See https://www.un.org/ruleoflaw/blog/document/the-secretary-generals-high-level-panel-report-on-threats-challenges-and-change-a-more-secure-world-our-shared-responsibility.
• Be aware of any availability bias, so, understand what you do NOT observe. Do not only construct a theory because data is available.

Decide:
• Practice constructive confrontation and follow a dialectical approach. What are the consequences if this is right? What are the consequences if it is wrong?
• Take a broad and multi-faceted view, also called a dragonfly view. Avoid the ‘Halo effect’ and give opportunities to mavericks.

Execute:
• Avoid over-confidence.
• Leave maximal initiative at the lowest level.
• Complement inductive and deductive scientific reasoning. The first should be executed on available data, the second on aspects where no data is available. It is not because there is no data that there should be no research.

Challenge:
• Automatically accept peer-reviewed falsification of a paper in the same journal.
• Also give funding to teams that are specialized in challenging entrenched ideas or that are specialized in falsification of already-accepted research. This means creating an environment where it is possible for teams to specialize in such ‘negative science’.
• Clearly understand the first principles of a theory and the possibility that an outlier may be a ‘paradigm-killer’.

Explore:
• Set up a system for ‘organized playing’ (in line with Google’s 20% rule8).
• Give researchers time, money and a forum to explore beyond the trodden paths, to play.

7. Concluding remarks
We started with the general widely documented observation that luck and opportunity often play an important role in success, in many instances much more than one realizes, across a number of fields, including financial trading, business, sports, art, music, literature, and science. We followed up with the logical implication that, since it is success that is in general rewarded, when luck is strong, then luck is rewarded rather than merit. Rewarding luck is likely

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8 This is explained in the prospectus of Google’s IPO: ‘We encourage our employees, in addition to their regular projects, to spend 20% of their time working on what they think will most benefit Google. This empowers them to be more creative and innovative. Many of our significant advances have happened in this manner.’ (https://www.sec.gov/Archives/edgar/data/1288776/000119312504073639/ds1.htm)
to promote a culture of gambling, while downplaying the importance of education, effort, qualitative process and persistence.

We suggested a number of mechanisms explaining the focus on success rather than merit in order to grant rewards. One among them stands out and dives deep in our evolutionary past: evolution ultimately rewards those species and individuals who have been able to transmit their genes. Gene replication and transmission is the ultimate measure of success from a genetic and biological point of view. If the transmission results more from luck than from fitness, nature does not care and the rewards will come in the form of more offspring, whatever the origin of success. Success is also the natural default metric of value, in the general absence of transparent information on merit, linking the problem of identifying the causes of success to the economics of asymmetric and imperfect information.

We then asked how to do better, which requires to unravel the true merits underlying success. For this, we identified three main classes of activities that require distinct approaches: (i) outcome based reward; (ii) risk-adjusted outcome based reward and (iii) prospective reward. The first class is characterized by a single outcome. In this case, the best (worst) achievers are clearly the luckiest (unluckiest), and are not the better skilled and more deserving ones. We showed quantitatively that only time can sort out the skilled from the lucky achievers. The second class was characterized by the option to obtain intermediate measurements, allowing monitoring performance and thus quantifying the contribution of stochasticity. Quantifying performance on a risk-adjusted basis completely removed the bias toward selecting lucky achievers and becomes equivalent to rewarding the process, as desired. In the third class, the environment is changing and history is no longer a faithful information base to predict the future. However, we showed that the past can be used to formulate future scenarios based on a deductive scientific approach. This led us to propose navigating into the future using the framework of complex adaptive systems, decomposing any action into five steps: observe, decide, execute, challenge and explore.

Finally, we have presented recommendations that derive from our analyses, for four domains: finance, tax policy, politics and science. In finance, a recommendation deriving logically from the above discussion is the establishment of simple regulations that make transparent the need for providing high quality service respecting the fiduciary principle (Bogle, 2009) as opposed to competition for bonuses. In tax policy, we proposed that the degree with which a taxation system is progressive should in fact reflect the relative role of luck versus merit and work in the level of income: the more luck, the more progressive should be taxation. It follows that different activities should be taxed differently, according to the amount of luck contributing to income. In politics, we were concerned by the significant level of luck and unaccountability of the political process and draw attention to the active research in new designs that could possibly remove chance and improve the global welfare. Last, in Science, where both luck, skill and hard work contribute, we analysed some of the existing imperfections in the reputation build-up and granting system and discussed several designs, inspired by market mechanisms.

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Appendix:

‘Should we reward process rather than success?’

A.1 Simulating the role of time in separating skill and luck in the ‘outcome based’ process.

We start from a heterogenous population of N agents, each one has an individual share of skill \( \mu_i \) and luck \( \sigma_i \). The agents participate in an activity, the outcome of which follows a GBM process. After a time-step \( \Delta T \), the success of an agent can be calculated from equation (3). As explained in section 4.2, this success has a skill part, equal to \( (\mu - \frac{\sigma^2}{2}) \Delta T \), but also a luck part proportional to \( \sigma_i \sqrt{\Delta T} \). Skill and luck are orthogonal, non-correlated by design. In line with Shockley’s findings, we sample both \( \mu_i \) and \( \sigma_i \) from lognormal distributions. As such, the whole population of agents is characterized by four parameters:

- \( \mu_{\text{skill}} \), the mean of the skills of the N agents;
- \( \sigma_{\text{skill}} \), the standard deviation of the skills of the N agents;
- \( \mu_{\text{luck}} \), the mean of the luck of the N agents;
- \( \sigma_{\text{luck}} \), the standard deviation of the luck of the N agents.

We sample N agents from this population, so that to each one is given a specific amount of skill \( (\mu_i) \) and luck \( (\sigma_i) \). Then, we let them act over a period \( \Delta T \), during which the evolution of their success follows a GBM process of the form (3), with the idiosyncratic \( \mu_i \) and \( \sigma_i \). Finally, we split up the population in deciles, each containing N/10 agents, according to their realized individual success after the time-step \( \Delta T \), and not using the “real” \( \mu_i \) and \( \sigma_i \) values of each of the agents, which are assumed not directly observable. We calculate the average of the skills \( \mu_i \) and the luck \( \sigma_i \) for each decile. The purpose of this simulation is to see under what conditions it is possible to separate “real” skill from “real” luck, based on one single observation of success, so as to simulate when outcome based reward can be used effectively.

The simulation is repeated for different periods \( \Delta T \), which we will call the “vetting period”, the period to assess the qualities of, or to “vet” the agent. The results are presented in figure A.1, for four different populations with increasing heterogeneity. As explained, each population is fully characterized by four different parameters, which are given in the uppermost subplot. The two subplots below give results for that same population. Here, the parameters are not repeated in order not to make the figures too busy.

Each subplot shows the results for eight different vetting periods: one day (1D), one week (1W), one month (1M), one quarter (1Q), half-a-year year (1H), one year (1Y), two years (2Y) and four years (4Y). In that respect, the four parameters that characterize the populations should be regarded as annualized numbers in the GBM process. The x-axis, which ranges from 1 to 10, differentiates between the different deciles, 1 is the most successful and 10 is the least successful decile after the vetting period. The y-axes give the average skill, luck and Sharpe ratio\(^9\) for the N/10 agents in each decile. The black dotted line shows the out-of-sample value for that population, meaning, independent of decile or vetting period.

\[^9\] Note that the skill per decile is defined as the arithmetic mean of the \( \mu_i \) of the agents in the decile, the luck is the square root of the arithmetic mean of the \( \sigma_i^2 \) of the agents in the decile, the Sharpe ratio is the skill per decile divided by the luck per decile. The Sharpe ratio is a standard measure of quality of financial investments, in the sense that it provides a theoretically founded risk-adjusted measure of performance.
Fig. A.1: Skill, luck and Sharpe ratio (defined as skill divided by luck) per decile over one year after different vetting periods $\Delta T$ (1 day, 1 week, 1 month, 1 quarter, half-a-year, one year, two years and four years) and for two different populations, one for each column. The black dotted line shows the out-of-sample value for the whole population.
A.2 Simulating the effect of intermediate observations

We follow the same basic model as in Appendix A.1, but, instead of using the direct outcome of the process as the measure for success, now we divide this by the estimated realized volatility. This Sharpe ratio will be our new proxy for success.

![Diagram](image)

Fig. A.2: Skill, luck and Sharpe ratio (defined as skill divided by luck) per decile after a one year vetting period $\Delta T$. The Sharpe ratio is used as the measure for success to rank the different agents in deciles. The different curves show the results for the different numbers of intermediary steps that are used to estimate the realized volatility. These should be compared to the green line for the same population in figure A.1. The black dotted line shows the out-of-sample value for the whole population.
Again, we split up the population in deciles, each containing N/10 agents, according to their realized individual Sharpe ratio after the time-step $\Delta T$, and we calculate the average of the skills $\mu_i$ and the luck $\sigma_i$ for each decile. The results for an increasing number of intermediary steps, and for a vetting period of one year, are presented in figure A.2. These can be compared to the green line for the same population in figure A.1.

A.3 Tools and systems in the literature

| Concept                     | Field                        | About                                                                 | Viewpoint | Reference                  |
|-----------------------------|------------------------------|----------------------------------------------------------------------|-----------|----------------------------|
| Direct adaptation           | System engineering           | Control system reacting when a threshold is crossed, like a thermostat: 'too hot' 'too cold' 'too hot'...             | Unconditional |                            |
| Black Swan                  | System engineering           | Exogenous unpredictable disturbance of large impact.                 | Unconditional | Taleb (2010)               |
| Prisoner’s dilemma/Stag hunt| Game theory                  | Tragedy of the commons/social dilemma: Nash equilibrium based on individual perspective and non-cooperation even though collaboration would end in a better outcome for every agent. | Unconditional |                            |
| Up-and-Down economics       | Journalism                   | Coverage of financial markets and economy: ‘went up’, ‘went down’.    | Unconditional | Krugman (1990)             |
| Illusion of Control         | Psychology                   | Estimation of personal success probability inappropriately higher than the objective probability.                   | Unconditional | Langer (1975)             |
| Just world hypothesis       | Psychology                   | Good things happen to people who do good things, bad things happen to people who do bad things.                   | Unconditional | Lerner and Montada (1998) |
| Ballistic action            | Psychology                   | Logic of Failure: Taking measures without checking the effect of these measures later.                          | Unconditional | Dornier et al. (1990)     |
| Expert system               | Control theory               | Expert control system based on a decision tree, ‘if … then, … else.’                                      | Retrospective |                            |
| CAPM                        | Finance                      | Capital Asset Pricing Model: pricing financial assets based on tangent portfolio.                                | Retrospective | Sharpe (1964)             |
| Replicating portfolio       | Finance                      | Derivative pricing based on dynamic replication and efficient markets, fundamental principal behind the Black-Scholes formula for option pricing. | Retrospective | Black and Scholes (1973) |
| Modern Portfolio Theory     | Finance                      | Mean variance analysis, mathematical framework for structuring a portfolio of financial assets accounting for diversification. | Retrospective | Markowitz (1952)         |
| Overfitting                 | Statistics                   | Datasnooping: spurious correlation found as the result of extensive data analysis, without any causation.        | Retrospective |                            |
| Martingale                  | Statistics                   | Random walk (or stochastic process) for which, at a particular time, the most probable next value, given all prior values, is equal to the present value. | Retrospective |                            |

Table A.1: Literature review: tools and systems based on outcome based reward and risk-adjusted outcome based reward
| Concept                  | Field                  | About                                                                 | Viewpoint | Reference           |
|-------------------------|------------------------|----------------------------------------------------------------------|------------|---------------------|
| Prediction error game   | Game theory            | A game theoretical framework based on understanding of the utility function of agents and decision makers in a geopolitical context. | Prospective | De Mesquita (2000) |
| Complex adaptive system | System engineering     | Self-learning control system inspired by biological evolution based on a scheme that changes based on reproduction, mutation, fitness function (genetic algorithm). | Prospective | Gell-Mann (1994)   |
| Dragon King              | System engineering     | Endogenous predictable disturbance of large impact. These events are the outcome of a dynamical systems progressively approaching an instability leading to a transition to another mode. | Prospective | Sorvetie and Oulion (2012) |
| Beyond markets and states | Economics              | Through communication and cooperation, institutions may self-organize beyond the market and the state. Complex systemic problems may best be solved by complex self-organized institutions. | Prospective | Ostrom (2012)      |
| An Engine, not a camera | Finance                | Financial and economic models are not merely descriptive but feed back to and influence reality. | Prospective | MacKenzie (2006)   |
| Reflexivity              | Finance                | Observers are part of the system observed: feedback loop between investors' perception and the environment. | Prospective | Soros (1998)       |
| EPPLS                    | Finance                | Log Periodic Power Law Singularity: estimation of a structural break in the future, time at risk. | Prospective | Sorvetie (2017)    |
| Kelly criterion          | Finance                | Optimizing the size of a bet, taking into account the gambler's edge or expectation of the odds. | Prospective | Kelly Jr (1956)     |
| Real options             | Finance                | Take into account future potential when valuing financial assets. | Prospective | Diet and Pindyck (1994) |
| Primum non nocere        | Medicine               | Hippocratic oath: First do no harm, justified by the Yellowstone effect. | Prospective | Malamud et al. (1998) |
| Structured Hierarchical MCDM | Strategy              | Structured Hierarchical Multi Criteria Decision Analysis: Evaluation of multiple conflicting, hierarchical criteria in decision making. | Prospective | Means and Sorvetie (2018) |
| Adaptive stance          | Strategy               | Counters predispositions and offers an effective methodological framework for managing, creating, shaping and interacting with complex systems. | Prospective | Grisogono and Radanovic (2011) |
| Auftragstaktik           | Strategy               | Mission command tactics, global mission carried out by local decisions. Strategic warfare based on Mao, Klauserits, Sun Tzu's Art of War, Napoleon | Prospective |                     |
| OODA loop                | Strategy               | Observe, orient, decide, act, use time as a weapon, be the fastest to complete the cycle from observation to action, act on information faster than the opponent. | Prospective | Coman (2004)       |
| Lean enterprise          | Strategy               | The company who acts on information faster is in the best position to win, business strategy based on John Boyd's OODA loop. | Prospective | Humble et al. (2015) |
| Homo Prospectus          | Psychology             | Forward Looking Man to whom consciousness is the generation of simulations about possible futures. | Prospective | Seligman et al. (2013, 2016) |
| Superforecasting         | Psychology             | Organizing forecasting tournaments to identify the distinctive features of good quality expert judgements and predictions. | Prospective | Tetlock and Gardner (2015) |
| Self-organized criticality | Statistical physics    | A dynamical system that tunes itself as it evolves towards criticality, well-known example is a sandpile. | Prospective | Bak et al. (1987) |
| Regression to the mean   | Statistics             | After a successful series of statistical independent observations (a hot streak), there is a high probability that success wanes and observations reverse to the mean. | Prospective | Galton (1888)       |
| Bayesian inference       | Statistics             | Use of Bayes' theorem to update probability for a hypothesis in real time while more information becomes available. | Prospective |                     |

Table A.2: Literature review: tools and systems based on prospective reward.