Talent vs Luck: the role of randomness in success and failure

A. Pluchino*, A. E. Biondo†, A. Rapisarda‡

Abstract

The largely dominant meritocratic paradigm of highly competitive Western cultures is rooted on the belief that success is due mainly, if not exclusively, to personal qualities such as talent, intelligence, skills, smartness, efforts, willfulness, hard work or risk taking. Sometimes, we are willing to admit that a certain degree of luck could also play a role in achieving significant material success. But, as a matter of fact, it is rather common to underestimate the importance of external forces in individual successful stories. It is very well known that intelligence (or, more in general, *talent* and personal qualities) exhibits a Gaussian distribution among the population, whereas the distribution of wealth - often considered a proxy of success - follows typically a power law (Pareto law), with a large majority of poor people and a very small number of billionaires. Such a discrepancy between a Normal distribution of inputs, with a typical scale (the average talent or intelligence), and the scale invariant distribution of outputs, suggests that some hidden ingredient is at work behind the scenes. In this paper, with the help of a very simple agent-based toy model, we suggest that such an ingredient is just randomness. In particular, we show that, if it is true that some degree of talent is necessary to be successful in life, almost never the most talented people reach the highest peaks of success, being overtaken by mediocre but sensibly luckier individuals. As to our knowledge, this counterintuitive result - although implicitly suggested between the lines in a vast literature - is quantified here for the first time. It sheds new light on the effectiveness of assessing merit on the basis of the reached level of success and underlines the risks of distributing excessive honors or resources to people who, at the end of the day, could have been simply luckier than others. With the help of this model, several policy hypotheses are also addressed and compared to show the most efficient strategies for public funding of research in order to improve meritocracy, diversity and innovation.

Keywords: Success, Talent, Luck, Randomness, Serendipity, Funding strategies.

1 Introduction

The ubiquity of power-law distributions in many physical, biological or socio-economical complex systems can be seen as a sort of mathematical signature of their strongly correlated dynamic behavior and their scale invariant topological structure [1, 2, 3, 4]. In socio-economic context,

*Department of Physics and Astronomy, University of Catania and INFN Sezione di Catania, Italy; alessandro.pluchino@ct.infn.it

†Dept. of Economics and Business, Univ. of Catania, Italy; ae.biondo@unict.it

‡Department of Physics and Astronomy, University of Catania and INFN Sezione di Catania, Italy; Complexity Science Hub Vienna; andrea.rapisarda@ct.infn.it

after Pareto's work [5, 6, 7, 8, 9], it is well known that the wealth distribution follows a power-law, whose typical long tailed shape reflects the deep existing gap between the rich and the poor in our society. A very recent report [10] shows that today this gap is far greater than it had been feared: eight men own the same wealth as the 3.6 billion people constituting the poorest half of humanity. If one considers the individual wealth as a proxy of success, one could argue that its deeply asymmetric and unequal distribution among people is either a consequence of their natural differences in talent, skill, competence, intelligence, ability or a measure of their willfulness, hard work or determination. Such an assumption is, indirectly, at the basis of the so-called *meritocratic paradigm*: it affects not only the way our society grants work opportunities, fame and honors, but also the strategies adopted by Governments in assigning resources and funds to those who are considered the most deserving individuals.

However, the previous conclusion appears to be in strict contrast with the accepted evidence that human features and qualities cited above are normally distributed among the population, i.e. follow a symmetric Gaussian distribution around a given mean. Further, there is nowadays an ever greater evidence about the fundamental role of chance, luck or, more in general, random factors, in determining successes or failures in our personal and professional lives. In particular, it has been shown that scientists have the same chance along their career of publishing their biggest hit [11]; that those with earlier surname initials are significantly more likely to receive tenure at top departments [12]; that one's position in an alphabetically sorted list may be important in determining access to over-subscribed public services [13]; that middle name initials enhance evaluations of intellectual performance [14]; that people with easy-to-pronounce names are judged more positively than those with difficult-to-pronounce names [15]; that individuals with noble-sounding surnames are found to work more often as managers than as employees [16]; that females with masculine monikers are more successful in legal careers [17]; that roughly half of the variance in incomes across persons worldwide is explained only by their country of residence and by the income distribution within that country [18]; that the probability of becoming a CEO is strongly influenced by your name or by your month of birth [19, 20, 21]; and that even the probability of developing a cancer, maybe cutting a brilliant career, is mainly due to simple bad luck [22].

In recent years many authors, among whom the statistician and risk analyst Nassim N. Taleb [23, 24], the investment strategist Michael Mauboussin [25] and the economist Robert H. Frank [26], have explored in several successful books the relationship between luck and skill in financial trading, business, sports, art, music, literature, science and in many other fields. They reach the conclusion that chance events play a much larger role in life than many people once imagined. Actually, they do not suggest that success is independent of talent and efforts, since in highly competitive arenas or 'winner-takes-all' markets, like those where we live and work today, people performing well are almost always extremely talented and hard-working. Simply, they conclude that talent and efforts are not enough: luck also matters, even if its role is almost always underestimated by successful people. This happens because randomness often plays out in subtle ways, therefore it is easy to construct narratives that portray success as having been inevitable. Taleb calls this tendency "narrative fallacy" [24], while the sociologist Paul Lazarsfeld adopts the terminology "hindsight bias". In his recent book "Everything Is Obvious: Once You Know the Answer" [27], the sociologist and network science pioneer Duncan J. Watts, suggests that both narrative fallacy and hindsight bias operate with particular force when people observe unusually successful outcomes and consider them as the necessary product of hard work and talent, while they mainly emerge from a complex and interwoven sequence of steps, each depending on precedent ones: if any of them had been different, an entire career or life trajectory would almost surely differ too.

In this paper, by adopting an agent-based approach, we try to quantify realistically the role of luck and talent in successful careers. In section 2, starting from a minimal number of assumptions, i.e. a Gaussian distribution of talent [28] and a multiplicative dynamics for both successes and failures [29], we propose a toy model, that we call "Talent vs Luck" (TvL) model, which mimics the evolution of careers of a group of people over a working period of 40 years. The model shows that, actually, randomness plays a fundamental role in selecting the most successful individuals. Of course, as one could expect, talented people are more likely to become rich, famous or important during their life with respect to poorly equipped ones. But - and this is a less intuitive rationale - ordinary people with a medium level of talent are statistically destined to be successful (i.e. to be placed along the tail of some power law distribution of success) much more than the most talented ones, provided that they are more blessed by fortune along their life. This fact is often observed in everyone common experience as pointed in refs.[23, 24, 26], but, to our knowledge, it is modelled and quantified here for the first time.

The success of the average-talented people strongly challenges the "meritocratic" paradigm and all those strategies and mechanisms, which give more rewards, opportunities, honors, fame and resources to people considered the best in their field [31, 34, 36]. The point is that, in the vast majority of cases, all evaluations of someone's talent are carried out *a posteriori*, just by looking at his/her performances - or at reached results - in some specific area of our society like sport, business, finance, art, science, etc. This kind of misleading evaluation ends up switching cause and effect, rating as the most talented people those who are, simply, the luckiest ones [30]. In line with this perspective, we already warned, in previous works, against such a kind of "naive meritocracy" and we showed the effectiveness of alternative strategies based on random choices in many different contexts, such as management, politics and finance [37, 38, 39, 40, 41, 42, 43, 44]. In section 3 we provide an application of our approach and sketch a comparison of possible public funds attribution schemes in the scientific research context. We study the effects of several distributive strategies, among which the "naively" meritocratic one, with the aim of exploring new ways to increase both the minimum level of success of most talented people in a community and the resulting efficiency of the public expenditure. We also explore, in general, how opportunities offered by the environment, as the education and income levels (i.e., external factors depending on the country and the social context where individuals come from) do matter in increasing probability of success. Final conclusive remarks close the paper.

2 The Model

In what follows we propose an agent-based model, called "Talent vs Luck" (TvL) model, which builds on a small set of very simple assumptions, aiming to describe the evolution of careers of a group of people influenced by lucky or unlucky random events.

We consider N individuals, with talent T_i (intelligence, skills, ability, etc.) normally distributed around a given mean m_T with a standard deviation σ_T, randomly placed in fixed positions within a squared world (see Fig.1) and surrounded by a certain number N_E of "moving" events (indicated by dots), someone lucky, someone else unlucky (neutral events are not considered in the model, since they have no relevant effects on the individual life). In Fig.1 we report these events as colored points: lucky ones, in green and with relative percentage p_L, and

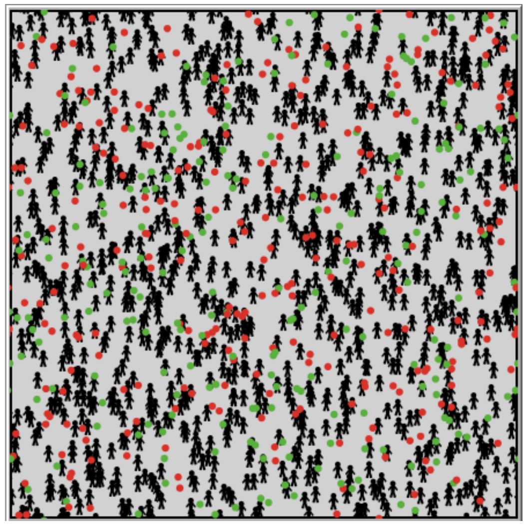

Figure 1: An example of initial setup for our simulations. $N = 1000$ individuals (agents), with different degrees of talent (intelligence, skills, etc.), are randomly located in their fixed positions within a square world. During each simulation, which covers several dozens of years, they are exposed to a certain number N_E of lucky (green circles) and unlucky (red circles) events, which move across the world following random trajectories (random walks). In this example $N_E = 500$. All simulations presented in this paper were realized within the NetLogo agent-based model environment [45].

unlucky ones, in red and with percentage $(100 - p_L)$. The total number of event-points N_E are uniformly distributed, but of course such a distribution would be perfectly uniform only for $N_E \to \infty$. In our simulations, typically will be $N_E \sim N/2$: thus, at the beginning of each simulation, there will be a greater random concentration of lucky or unlucky event-points in different areas of the world, while other areas will be more neutral. The further random movement of the points inside the square lattice, the world, does not change this fundamental features of the model, which exposes different individuals to different amount of lucky or unlucky events during their life, regardless of their own talent.

For a single simulation run, a working life period P of 40 years (from the age of twenty to the age of sixty) is considered, with a time step δ_t equal to six months. At the beginning of the simulation, all agents are endowed with the same amount $C_i = C(0)\ \forall i = 1, ..., N$ of capital, representing their starting level of success/wealth. This choice has the evident purpose of not offering any initial advantage to anyone. While the agents' talent is time-independent, agents' capital changes in time. During the time evolution of the model, i.e. during the considered agents' life period, all event-points randomly move around the world and, in doing so, they possibly intersect the position of some agent. Depending on such an occurrence, at a given time step t (i.e. every six months), there are three different possible actions for a given agent A_k:

1. No event-point intercepts the position of agent A_k: this means that no relevant facts have happened during the last six months; agent A_k does not perform any action.

2. A lucky event intercepts the position of agent A_k: this means that a lucky event has occurred during the last six month; as a consequence, agent A_k doubles her capital/success with a probability proportional to her talent T_k. It will be $C_k(t) = 2C_k(t-1)$ only if

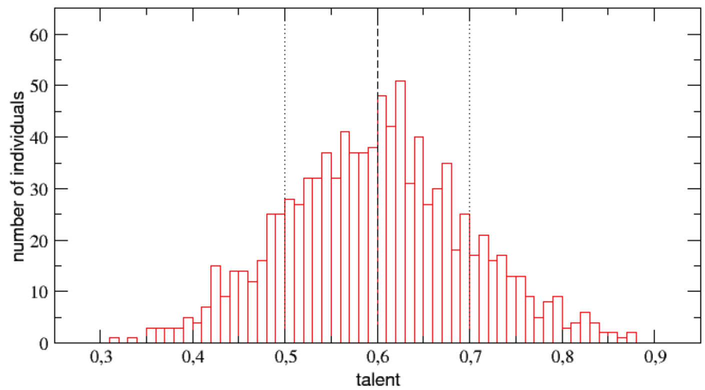

Figure 2: Normal distribution of talent among the the population (with mean $m_T = 0.6$, indicated by a dashed vertical line, and standard deviation $\sigma_T = 0.1$ - the values $m_T \pm \sigma_T$ are indicated by two dotted vertical lines). This distribution does not change during the simulation.

$rand[0, 1] < T_k$, i.e. if the agent is smart enough to profit from his/her luck.

3. An unlucky event intercepts the position of agent A_k: this means that an unlucky event has occurred during the last six month; as a consequence, agent A_k halves her capital/success, i.e. $C_k(t) = C_k(t-1)/2$.

The previous agents' rules are intentionally simple and can be considered widely shareable, since they are based on the common sense evidence that success, in everyone life, has the property to both grow or decrease very rapidly. Furthermore, these rules gives a significant advantage to highly talented people, since they can make much better use of the opportunities offered by lucky opportunities. What we will see in the following is that such an advantage is a *necessary, but not a sufficient*, condition to reach a very high degree of success.

2.1 Single run results

In this subsection we present the results of a typical single run simulation. Actually, these results are very robust so, as we will show later, they can be considered largely representative of the general framework emerging from the our model.

Let us consider $N = 1000$ agents, with a starting equal amount of capital $C(0) = 10$ (in dimensionless units) and with a fixed talent $T_i \in [0, 1]$, which follows a normal distribution with mean $m_T = 0.6$ and standard deviation $\sigma_T = 0.1$ (see Figure 2). As previously written, the simulation spans a time period of $P = 40$ years, evolving through time steps of six months each, for a total of $I = 80$ iterations. In this simulation we consider $N_E = 500$ event-points, with a percentage $p_L = 50\%$ of lucky events.

At the end of the simulation, as shown in panel (a) of Figure 3, we find that the simple dynamical rules of the model are able to produce an unequal distribution of capital/success, with a large amount of poor (unsuccessful) agents and a small number of very rich (successful) ones. Plotting the same distribution in log-log scale in panel (b) of the same Figure, a Pareto-like power-law distribution is observed, well fitted by the function $y(C) \sim C^{-1.27}$. Therefore, despite the normal distribution of talent, the TvL model seems able to capture the first important feature

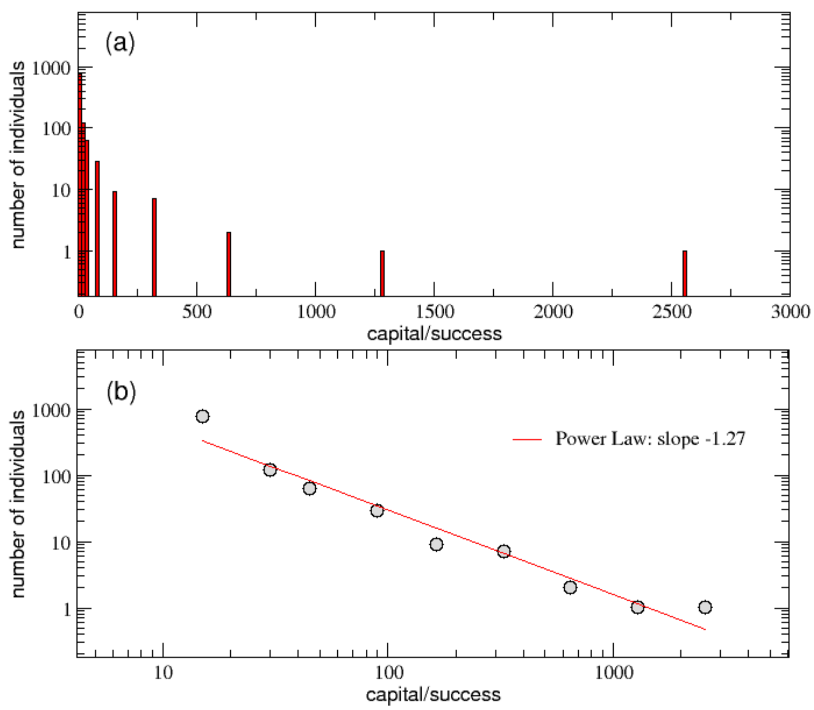

Figure 3: Final distribution of capital/success among the population, both in log-lin (a) and in log-log (b) scale. Despite the normal distribution of talent, the distribution of success - as visible in panel (b) - can be well fitted with a power-law curve with slope -1.27. We also verified that the capital/success distribution follows the Pareto's "80-20" rule, since 20% of the population owns 80% of the total capital, while the remaining 80% owns the 20% of the capital.

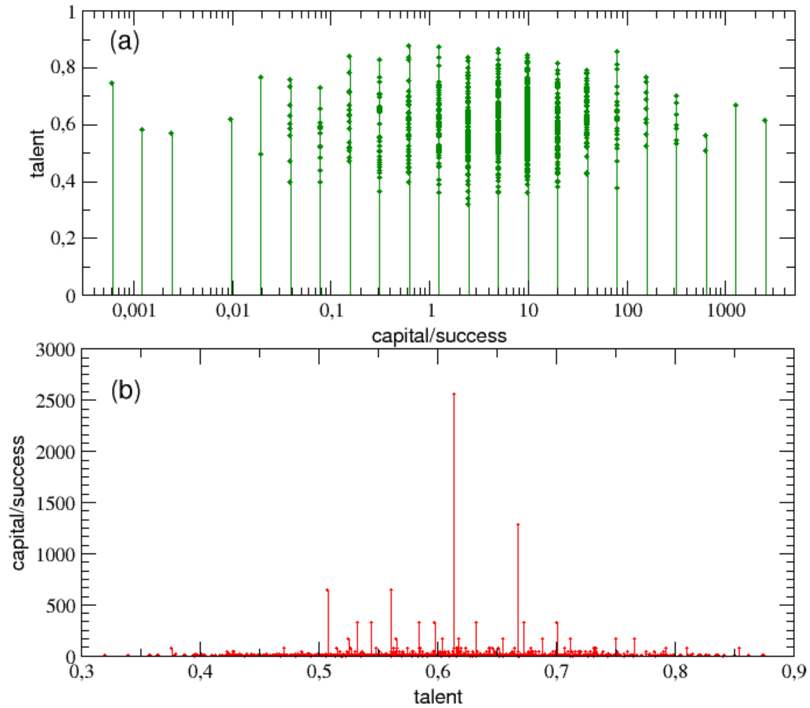

Figure 4: In panel (a) talent is plotted as function of capital/success (in logarithmic scale for a better visualization): it clearly appears that the most successful individuals are not the most talented ones. Notice that, having used an integer initial capital equal for all the agents, the dynamical evolution of the system groups them to discontinuous values of the capital/success for $t > 0$. In panel (b), vice-versa, capital/success is plotted as function of talent: here, it can be further appreciated the fact that the most successful agent, with $C_{max} = 2560$, has a talent only slightly greater than the mean value $m_T = 0.6$, while the most talented one has a capital/success lower than $C = 1$ unit, much less of the initial capital $C(0)$. See text for further details.

observed in the comparison with real data: the deep existing gap between rich and poor and its scale invariant nature. In particular, in our simulation, only 4 individuals have more than 500 units of capital and the 20 most successful individuals hold the 44% of the total amount of capital, while almost half of the population stay under 10 units. Globally, the Pareto's "80-20" rule is respected, since the 80% of the population owns only the 20% of the total capital, while the remaining 20% owns the 80% of the same capital. Although this disparity surely seems unfair, it would be to some extent acceptable if the most successful people were the most talented one, so deserving to have accumulated more capital/success with respect to the others. But are things really like that?

In panels (a) and (b) of Figure 4, respectively, talent is plotted as function of the final capital/success and vice-versa. Looking at both panels, it is evident that, on one hand, the most successful individuals are not the most talented ones and, on the other hand, the most talented individuals are not the most successful ones. In particular, the most successful individual, with $C_{max} = 2560$, has a talent $T^* = 0.61$, only slightly greater than the mean value $m_T = 0.6$, while the most talented one ($T_{max} = 0.89$) has a capital/success lower than 1 unit ($C = 0.625$).

As we will see more in detail in the next subsection, such a result is not a special case, but

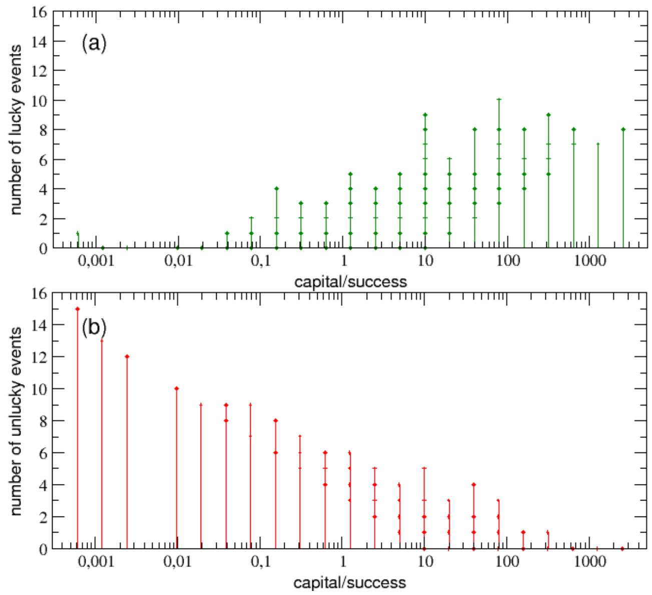

Figure 5: (a) Total number of lucky events or (b) unlucky events as function of the capital/success of the agents. The plot shows the existence of a strong correlation between success and luck: the most successful individuals are also the luckiest ones, while the less successful are also the unluckiest ones. Again, having used an initial capital equal for all the agents, it appears that several events are grouped on discontinuous values of the capital/success.

it is rather the rule for this kind of system: the maximum success never coincides with the maximum talent, and vice-versa. Moreover, such a misalignment between success and talent is disproportionate and highly nonlinear. In fact, the average capital of all people with talent $T > T^*$ is $C \sim 20$: in other words, the capital/success of the most successful individual, who is moderately gifted, is 128 times greater than the average capital/success of people who are more talented than him. We can conclude that, if there is not an exceptional talent behind the enormous success of some people, another factor is probably at work. Our simulation clearly shows that such a factor is just pure luck.

In Figure 5 the number of lucky and unlucky events occurred to all people during their working lives is reported as a function of their final capital/success. Looking at panel (a), it is evident that the most successful individuals are also the luckiest ones. On the contrary, looking at panel (b), it results that the less successful individuals are also the unluckiest ones. In other words, in the face of the absence of correlation between success and talent, there is a very strong correlation between success and luck. Notice that in panel (a) of this figure is reported the total number of lucky events occurred to the agents and not just those that they took advantage of, proportionally to their talent.

It is also interesting to look at the time evolution of the success/capital of both the most successful individual and the less successful one, compared with the corresponding sequence of lucky or unlucky events occurred during the 40 years (80 time steps, one every 6 months) of their working life. This can be observed, respectively, in the left and the right part of Figure 6. Differently from the panel (a) of Figure 5, in the bottom panels of this figure only lucky events that agents have taken advantage of thanks to their talent, are shown.

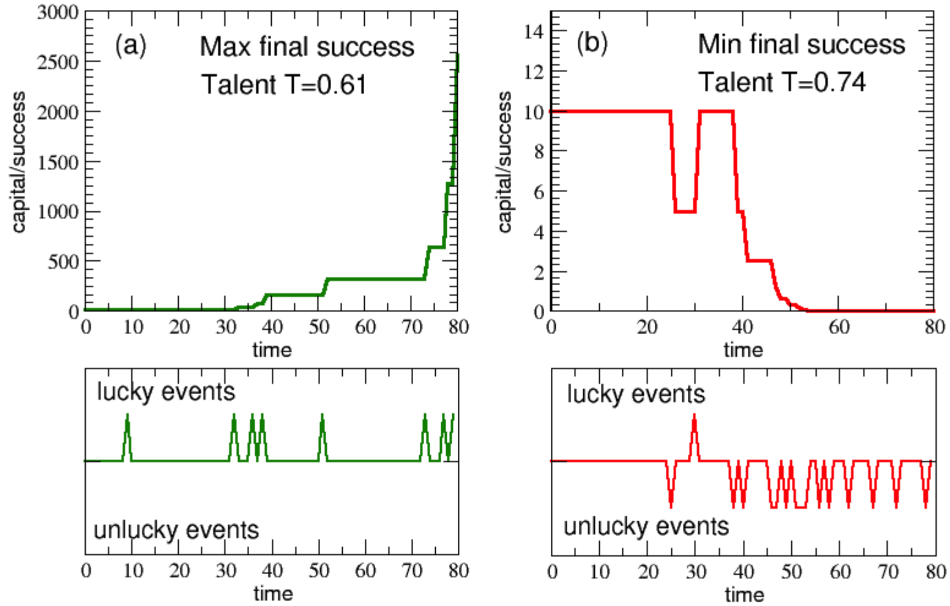

Figure 6: (a) Time evolution of success/capital for the most successful individual and (b) for the less successful one, compared with the corresponding sequences of lucky or unlucky events occurred during their working lives. The time occurrence of these events is indicated, in the bottom panels, with upwards or downwards spikes.

In panels (a), concerning the moderately talented but most successful individual, it clearly appears that, after about a first half of his working life with a low occurrence of lucky events (bottom panel), and then with a low level of capital (top panel), a sudden concentration of favorable events between 30 and 40 time steps (i.e. just before the age of 40 of the agent) produces a rapid increase in capital, which becomes exponential in the last 10 time steps (i.e. the last 5 years of the agent's career), going from $C = 320$ to $C = 2560$.

On the other hand, looking at (top and bottom) panels (b), concerning the less successful individual, it is evident that a particularly unlucky second half of his working life, with a dozen of unfavorable events, progressively reduces the capital/success bringing it at its final value of $C = 0.00061$. It is interesting to notice that this poor agent had, however, a talent $T = 0.74$ which was greater than that of the most successful agent. Clearly, good luck made the difference. And, if it is true that the most successful agent has had the merit of taking advantage of all the opportunities presented to him (in spite of his average talent), it is also true that if your life is as unlucky and poor of opportunities as that of the other agent, even a great talent becomes useless against the fury of misfortune.

All the results shown in this subsection for a single simulation run are very robust and, as we will see in the next subsection, they persist, with small differences, if we repeat many times the simulations starting with the same talent distribution, but with a different random positions of the individuals.

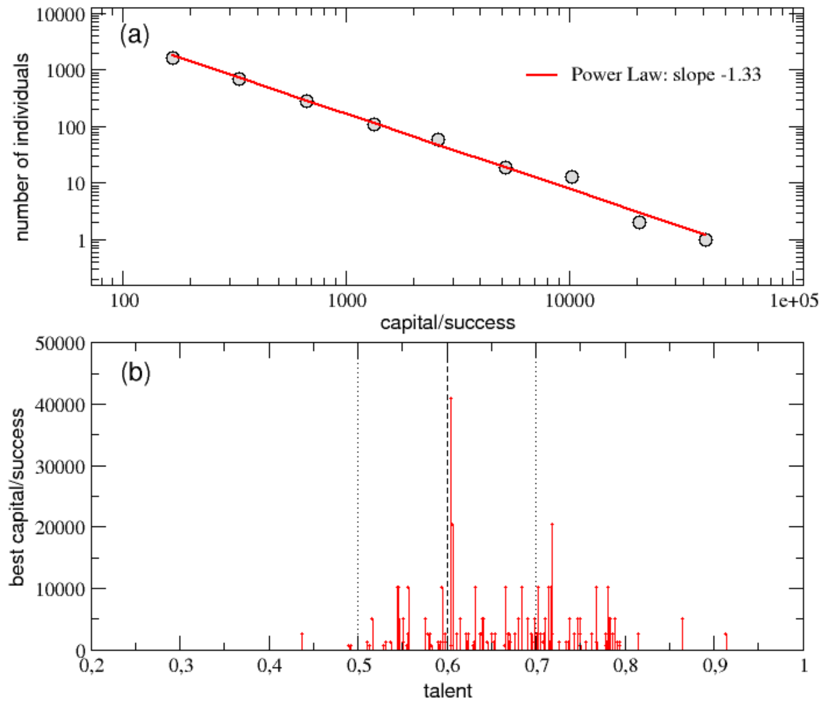

Figure 7: Panel (a): Distribution of the final capital/success calculated over 100 runs for a population with different random initial conditions. The distribution can be well fitted with a power-law curve with a slope -1.33. Panel (b): The final capital of the most successful individuals in each of the 100 runs is reported as function of their talent. People with a medium-high talent result to be, on average, more successful than people with low or medium-low talent, but very often the most successful individual is a moderately gifted agent and only rarely the most talented one. The m_T value, together with the values $m_T \pm \sigma_T$, are also reported as vertical dashed and dot lines respectively.

2.2 Multiple runs results

In this subsection we present the global results of a simulation averaging over 100 runs, each starting with different random initial conditions. The values of the control parameters are the same of those used in the previous subsection: $N = 1000$ individuals, $m_T = 0.6$ and $\sigma_T = 0.1$ for the normal talent distribution, $I = 80$ iteration (each one representing $\delta_t = 6$ months of working life), $C(0) = 10$ units of initial capital, $N_E = 500$ event-points and a percentage $p_L = 50\%$ of lucky events.

In panel (a) of Figure 7, the global distribution of the final capital/success for all the agents collected over the 100 runs is shown in log-log scale and it is well fitted by a power law curve with slope -1.33. The scale invariant behavior of capital and the consequent strong inequality among individuals, together with the Pareto's "80-20" rule observed in the single run simulation, are therefore conserved also in the case of multiple runs. Indeed, the gap between rich (successful) and poor (unsuccessful) agents has even increased, since the capital of the most successful people surpass now the 40000 units.

This last result can be better appreciated looking at panel (b), where the final capital of the most successful individuals only, for each one of the 100 runs, is reported as function of their

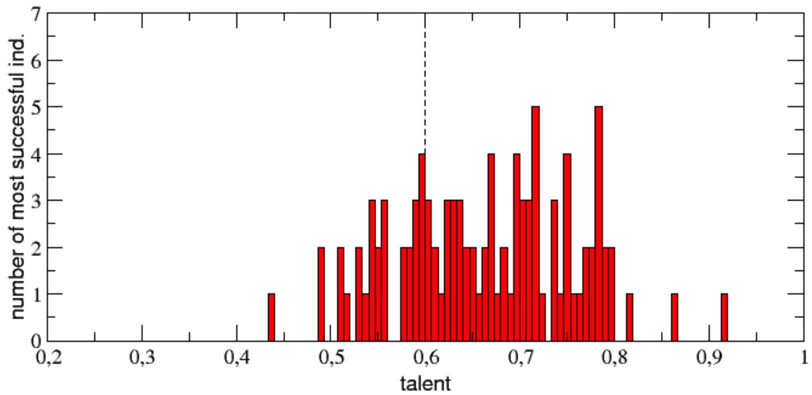

Figure 8: Skewed talent distribution of the most successful individuals calculated over 100 runs. The mean value $m_T = 0.6$ is reported for comparison as a vertical dashed line.

talent. The best performance was realized by an agent with a talent $T^* = 0.6048$, practically coinciding with the mean of the talent distribution ($m_T = 0.6$), who reached a peak of capital $C_{best} = 40960$. On the other hand, the most talented among the most successful individuals, with a talent $T_{max} = 0.91$, accumulated a capital of $C = 2560$, equal to only 6% of C_{best}.

To address this point in more detail, in Figure 8 we plot the talent distribution of the best performers calculated over 100 runs. The distribution is clearly skewed to the right of the talent axis, with a mean value of $T_{av} = 0.66$: this confirms, on one hand, that a medium-high talent is often necessary to reach a great success; but, on the other hand, it also indicates that it is almost never sufficient, since agents with the highest talent (e.g. with $T > m_T + 2\sigma_T$, i.e. with $T > 0.8$) result to be the best performers in their run only in 3% of cases, and their capital/success never exceeds the 13% of C_{best}.

This picture is further corroborated by the comparison between the average capital/success $C_{mt} \sim 63$, over 100 runs, of most talented people and the corresponding average capital/success $C_{at} \sim 33$ of people with talent very close to the mean m_T. We found in both cases quite small values (although greater than the initial capital $C(0) = 10$), but the fact that $C_{mt} > C_{at}$ indicates that, during their working life, most talented individuals have, on average, more success than moderately gifted people.

However, it is a fact that the absolute best performer over the 100 simulation runs is a mediocre agent, with a talent $T = 0.6$ perfectly aligned with the average, but with a final success $C_{best} = 40960$ which is 650 times greater than C_{mt}. This occurs just because, at the end of the story, she was just luckier than the others. Indeed, very lucky, as it is shown in Figure 9, where the increase of her capital/success during her working life is shown, together with the impressive sequence of lucky (and only lucky) events of which, despite the lack of particular talent, she was able to take advantage of during her career.

Summarizing, what has been found up to now is that, in spite of its simplicity, the TvL model seems able to account for many of the features characterizing, as discussed in the introduction, the largely unequal distribution of richness and success in our society, in evident contrast with the Gaussian distribution of talent among human beings. At the same time, the model shows, in quantitative terms (for the first time as far to our knowledge), that a great talent is not

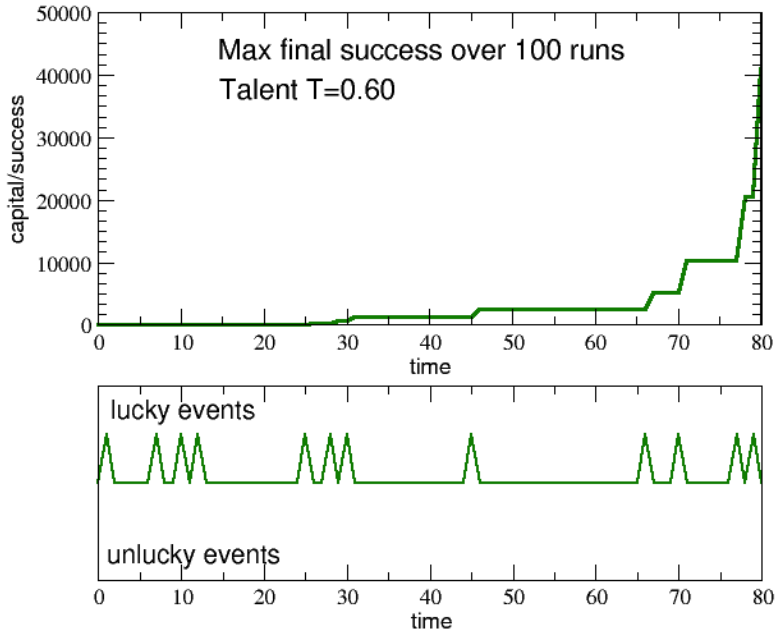

Figure 9: Time evolution of success/capital for the most successful (but moderately gifted) individual over the 100 simulation runs, compared with the corresponding unusual sequence of lucky events occurred during her working life.

sufficient to guarantee a successful career and that, instead, less talented people are very often able to reach the top of success - another frequent "stylized fact" of real life [23, 24, 26].

The key point, which intuitively explains how it may happen that moderately gifted individuals achieve (so often) far greater honors and success than much more talented ones, is the hidden and often underestimated role of luck, as resulting from our simulations.

In the next section we will explore the possibilities offered by our toy model to investigate in detail new and more efficient strategies and policies to improve the average performance of a population, implementing more efficient ways of distributing prizes and resources.

3 Effective strategies to counterbalance luck

The results presented in the previous section are strongly consistent with largely documented empirical evidences, discussed in the introduction, which firmly question the naively meritocratic assumption claiming that the natural differences in talent, skill, competence, intelligence, hard work or determination are the only causes of success. As we have shown, luck also matters and it can play a very important role. The interpretative point is that, being individual qualities difficult to be measured (in many cases hardly defined in rigorous terms), the meritocratic strategies used to assign honors, funds or rewards are often based on individual performances, valued in terms of personal wealth or success. Eventually, such strategies exert a further reinforcing action and pump up the wealth/success of the luckiest individuals through a positive feedback mechanism, which resembles the famous "rich get richer" process (also known as "Matthew effect"

[32, 33]), with an unfair final result.

Let us consider, for instance, a publicly-funded research granting council with a fixed amount of money at its disposal. In order to increase the average impact of research, is it more effective to give large grants to a few apparently excellent researchers, or small grants to many more apparently ordinary researchers? A recent study [34], based on the analysis of four indices of scientific impact involving publications, found that impact is positively, but only weakly, related to funding. In particular, impact per dollar was lower for large grant-holders and the impact of researchers who received increases in funding did not increase in a significant way. The authors of the study conclude that scientific impact (as reflected by publications) is only weakly limited by funding and suggest that funding strategies targeting diversity, rather than "excellence", are likely to be more productive. A more recent contribution [35] showed that, both in terms of the quantity of papers produced and of their scientific impact, the concentration of research funding generally produces diminishing marginal returns and also that the most funded researchers do not stand out in terms of output and scientific impact. Actually, such conclusions should not be a surprise in the light of the other recent finding [11] that impact, as measured by influential publications, is distributed randomly within a scientist's temporal sequence of publications. In other words, if luck matters, and if it matters more than we are willing to admit, it is not strange that meritocratic strategies reveal less effective than expected, in particular if we try to evaluate merit *ex-post*.

As anticipated in the introduction, in previous studies we already warned against this sort of "naive meritocracy", showing the effectiveness of alternative strategies based on random choices in management, politics and finance. In what follows, we will present some preliminary results, obtained by the TvL model, which show how to increase the minimum level of success of the most talented people in a world where luck is important and serendipity is often the cause of important discoveries.

3.1 Serendipity, innovation and efficient funding strategies

The term "serendipity" is commonly used in the literature to refer to the historical evidence that very often researchers make unexpected and beneficial discoveries by chance, while they are looking for something else [46, 47]. There is a long anecdotical list of discoveries made just by lucky opportunities: from penicillin by Alexander Fleming to radioactivity by Marie Curie, from cosmic microwave background radiation by radio astronomers Arno Penzias and Robert Woodrow Wilson to the graphene by Andre Geim and Kostya Novoselov. Therefore, many thinks that curiosity-driven research should always be funded because the beauty of research is that nobody can really know or predict where it can end.

Is it possible to quantify the role of serendipity? Which are the most efficient ways to stimulate serendipity? Serendipity can take on many forms, and it is difficult to constrain and quantify. That is why, so far, academic research has focused on serendipity in science mainly as a philosophical idea. But things are changing. The European Research Council has recently given to the biochemist Ohid Yaqub a 1.7 million US dollars grant to quantify the role of serendipity in science [48]. Yaqub found that it is possible to classify serendipity into four basic types [49] and that there may be important factors affecting its occurrence. His conclusions seem to agree with the believing that the commonly adopted - apparently meritocratic - strategies, which pursuit excellence and drive out diversity, seem destined to be loosing and inefficient [50, 51, 52, 53, 54, 55]. The reason is that they cut out *a priori* researches that initially appear less promising but that, thanks also to serendipity, could be extremely innovative *a posteriori*.

From this perspective, we want to use the TvL model, which naturally incorporates luck (and therefore also serendipity) as a quantitative tool for policy, in order to explore, in this subsection, the effectiveness of different funding scenarios. In particular, in contexts where, as above discussed, mediocre-but-lucky people are often more successful than more-gifted-but-unlucky individuals, it is important to evaluate the efficiency of funding strategies in preserving a minimum level of success also for the most talented people, who are expected to produce the most progressive and innovative ideas.

Starting from the same parameters setup used in subsection 2.2, i.e.$N = 1000$, $m_T = 0.6$, $\sigma_T = 0.1$, $I = 80$, $\delta_t = 6$, $C(0) = 10$, $N_E = 500$, $p_L = 50\%$ and 100 simulation runs, let us imagine that a given total funding capital F_T is periodically distributed among individuals following different criteria. For example, funds could be assigned:

1. in equal measure to all (*egalitarian criterion*), in order to foster diversity;
2. only to a given percentage of the most successful ("best") individuals (*elitarian criterion*), which has been previously referred to "naively" meritocratic, for it distributes funds to people according to their past performance;
3. by distributing a "premium" to a given percentage of the most successful individuals and the remaining amount in smaller equal parts to all the others (*mixed criterion*);
4. only to a given percentage individuals, randomly selected (*selective random criterion*);

We realistically assume that the total capital F_T will be distributed every 5 years, during the 40 years spanned by each simulation run, so that $F_T/8$ units of capital will be allocated from time to time. Thanks to the periodic injection of these funds, we intend to maintain a minimum level of resources for the most talented agents. Therefore, a good indicator, for the effectiveness of the adopted funding strategy, could be the number N_T, averaged over the 100 simulation runs, of individuals with talent $T > m_T + \sigma_T$ and with final success/capital greater than the initial one, i.e. $C_{end} > C(0)$. Another important point in favor of this indicator is its robustness: we have checked that repeating the set of 100 simulations, the variation in the value of N_T obtained, discussed below, remains under 2%.

In the multiple runs simulation presented in section 2.2 we have already shown that, in absence of funding, the best performance was scored by very lucky agents with a talent close to the mean, while the capital/success of the most talented people always remained very low. In particular, their average capital over the 100 runs was $C_{mt} \sim 63$. Looking at the average number, say N_{T0}, of individuals with talent $T > 0.7$ and with final success/capital $C_{end} > 10$, one finds that $N_{T0} = 51$. This means that, on average, only a percentage $P_{T0} \sim 32\%$ of the total number of agents with $T > 0.7$ (who are, on average, ~ 160) reaches, at the end of the simulation, a capital/success greater then the initial one. Hence, in order to compare the efficiency of different funding strategies, the increment in the average percentage P_T of talented people which, during their career, increase their initial capital/success should be calculated with respect to P_{T0}. Let us define this increment as $P_T^* = P_T - P_{T0}$. Finally, if one considers the ratio between P_T^* and the total invested capital F_T^*, which includes the initial capital $C(0) * N$ (1000 units) given to each individual at the beginning of each simulation run and the additional capital F_T distributed among all the agents during the 40 years, it is possible to obtain an *efficiency index* E, which

FUNDING-TARGET	NORM EFF INDEX	% SUCC.TAL.IND.	% INCREMENT	TOTAL FUNDING
ALL EQUAL 1u	1,00	69,48	37,43	9000u
10% RANDOM 5u	0,85	49,83	17,78	5000u
25% RANDOM 5u	0,79	68,00	35,95	11000u
ALL EQUAL 2u	0,74	84,02	51,97	17000u
50% RANDOM 5u	0,58	82,91	50,86	21000u
25% BEST 5u, OTHERS 1u	0,55	70,83	38,78	17000u
25% BEST 10u, OTHERS 1u	0,37	73,44	41,39	27000u
ALL EQUAL 5u	0,37	94,40	62,35	41000u
25% RANDOM 20u	0,31	84,74	52,69	41000u
50% BEST 5u	0,25	54,26	22,21	21000u
25% BEST 10u, OTHERS 5u	0,21	94,82	62,77	71000u
25% BEST 5u	0,20	41,08	9,03	11000u
25% BEST 10u	0,12	42,33	10,28	21000u
10% BEST 5u	0,10	34,14	2,09	5000u
25% BEST 15u	0,09	43,51	11,46	31000u
25% BEST 20u	0,07	44,26	12,21	41000u
10% BEST 10u	0,06	34,41	2,36	9000u
10% BEST 20u	0,04	34,98	2,93	17000u
NO FUNDING	0,00	32,05	0,00	1000u

Figure 10: Funding strategies Table. The outcomes of the normalized efficiency index E_{norm} are reported (2nd column) in decreasing order, from top to bottom, for several funding distribution strategies with different targets (1st column). The corresponding values of both the percentage P_T of successful talented people and its net increase P_T^* with respect to the "no funding" case, averaged over the 100 simulation runs, are also reported in the third and fourth columns respectively. Finally, the total capital F_T^* invested in each run, is visible in the last column.

quantifies the increment of sufficiently successful talented people per unit of invested capital, defined as $E = P_T^*/F_T^*$.

In the table shown in Figure 10, we report the efficiency index (2nd column) obtained for several funding distribution strategies, each one with a different funding target (1st column), together with the corresponding values of P_T (3rd column) and P_T^* (4th column). The total capital F_T^* invested in each run is also reported in the last column. The efficiency index E has been normalized to its maximum value E_{max} and the various records (rows) have been ordered for decreasing values of $E_{norm} = E/E_{max}$. The same scores for E_{norm} are also reported in the form of a histogram in Figure 11, as a function of the adopted funding strategies. Thanks to the statistical robustness of P_T, which shows fluctuations smaller than 2%, the results reported for the efficiency index E_{norm} are particularly robust.

Looking at the table and at the relative histogram of Figure 11, it is evident that, if the goal is to reward the most talented persons (thus increasing their final level of success), it is much more convenient to distribute periodically (even small) equal amounts of capital to all individuals rather than to give a greater capital only to a small percentage of them, selected through their level of success - already reached - at the moment of the distribution.

On one hand, the histogram shows that the "egalitarian" criterion, which assigns 1 unit of capital every 5 years to all the individuals is the most efficient way to distributed funds, being $E_{norm} = 1$ (i.e. $E = E_{max}$): with a relatively small investment F_T^* of 9000 units, it is possible to double the percentage of successful talented people with respect to the "no funding" case,

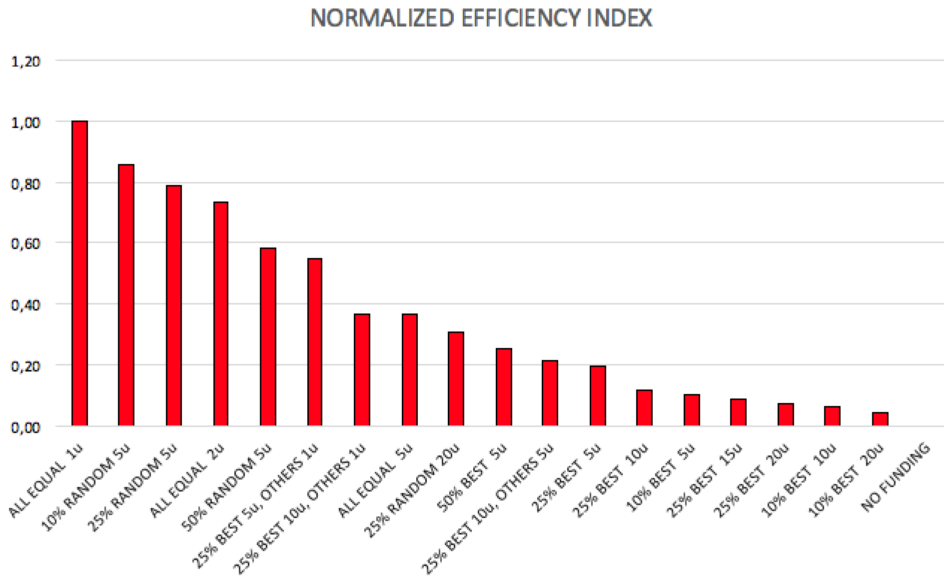

Figure 11: Normalized Efficiency index for several funding strategies. The values of the normalized efficiency index E_{norm} are reported as function of the different funding strategies. The figure shows that for increasing the success of a larger number of talented people with $C_{end} > C(0)$, it is much more efficient to give a small amount of funds to many individuals instead og giving fund in other more selective ways.

bringing it from $P_{T0} = 32.05\%$ to $P_T = 69.48\%$, with a net increase $P_T^* = 37.43\%$. Considering an increase of the total invested capital (for example, setting the egalitarian quotas to 2 or 5 units), this strategy also ensures a further increment in the final percentage of successful talented people P_T (from 69.48% to 84.02% and to 94.40%), even if the normalized efficiency progressively decreases from $E_{norm} = 1$ to $E_{norm} = 0.74$ and to $E_{norm} = 0.37$.

On the other hand, the "elitarian" strategies which assign every 5 years more funds (5, 10, 15 or 20 units) only to the best 50%, 25% or even 10% of the already successful individuals, are all at the bottom of the ranking, with $E_{norm} < 0.25$: in all of these cases, the net increase P_T^* in the final number of successful talented people with respect to the "no funding" case remains very small (in almost all the cases smaller than 20%), often against a much larger invested capital if compared to that of the egalitarian strategy. These results do reinforce the thesis that this kind of approach is only apparently - that is naively - meritocratic.

It is worth noticing that the adoption of a "mixed" criterion, i.e. assigning a "meritocratic" funding share to a certain percentage of the most successful individuals, for instance 25%, and distributing the remaining funds in equal measure to the rest of people, gives back better scores for the efficiency index values with respect to the "naively meritocratic" approach. However, the performance of this strategy is not able to overtake the "egalitarian" criterion. As it clearly appears - for example - by the comparison between the sixth and the fourth rows of the funding table, in spite of the same overall investment of 17000 units, the value of P_T obtained with the mixed criterion stays well below the one obtained with the egalitarian approach (70.83% against 84.02%), as also confirmed by the values of the corresponding efficiency index E_{norm} (0.55 against 0.74).

If one considers psychological factors (not modeled in this study), a mixed strategy could be revalued with respect to the egalitarian one. Indeed, the premium reward - assigned to the more successful individuals - could induce all agents towards a greater commitment, while the equally distributed part would play a twofold role: at the individual level, it would act in fostering diversity and providing unlucky talented people with new chances to express their potential, while feeding serendipity at the aggregate level, thus contributing to the progress of research and of the whole society.

Finally, looking again at the funding strategy table, it is also worthwhile to stress the surprising high efficiency of the random strategies, which occupy two out of the three best scores in the general ranking. It results that, for example, a periodic reward of 5 units for only the 10% of randomly selected individuals, with a total investment of just 5000 units, gives a net increase $P_T^* = 17,78\%$, which is greater than almost all those obtained with the elitarian strategies. Furthermore, increasing to 25% the percentage of randomly funded people and doubling the overall investment (bringing it to 11000 units), the net increase $P_T^* = 35.95\%$ becomes comparable to that obtained with the best egalitarian strategy, first in the efficiency ranking. It is striking to notice that this latter score for P_T^* is approximately four times grater than the value ($P_T^* = 9.03\%$) obtained with the elitarian approach (see 12th row in the table), distributing exactly the same capital (11000 units) to exactly the same number of individuals (25% of the total). The latter is a further confirmation that, in complex social and economical contexts where chance plays a relevant role, the efficiency of alternative strategies based on random choices can easily overtake that of standard strategies based on the "naively meritocratic" approach. Such a counterintuitive phenomenon, already observed in management, politics and finance ([37, 38, 39, 40, 41, 42, 43, 44]), finds therefore new evidence also in the research funding context.

The results of the TvL model simulations presented in this subsection, have focused on the importance of external factors (as, indeed, efficient funding policies) in increasing the opportunities of success for the most talented individuals, too often penalized by unlucky events. In the next subsection we investigate to what extent new opportunities can be originated by changes in the environment as for example the level of education or other stimuli received by the social context where people live or come from.

3.2 The importance of the environment

First, let us to estimate the role of the average level of education among the population. Within the TvL model, the latter could be obtained by changing the parameters of the normal distribution of talent. Actually, assuming that talent and skills of individuals, if stimulated, could be more effective in exploiting new opportunities, an increase in either the mean m_T or the standard deviation σ_T of the talent distribution could be interpreted as the effect of policies targeted, respectively, either at raising the average level of education or at reinforcing the training of the most gifted people.

In the two panels of Figure 12 we report the final capital/success accumulated by the best performers in each of the 100 runs, as function of their talent. The parameters setup is the same than in subsection 2.2 ($N = 1000$, $I = 80$, $\delta_t = 6$, $C(0) = 10$, $N_E = 500$ and $p_L = 50\%$) but with different moments for the talent distributions. In particular, in panel (a) we left unchanged $m_T = 0.6$ but increased $\sigma_T = 0.2$, while in panel (b) we made the opposite, leaving $\sigma_T = 0.1$ but increasing $m_T = 0.7$. In both the cases, a shift on the right of the maximum success peaks can be appreciated, but with different details.

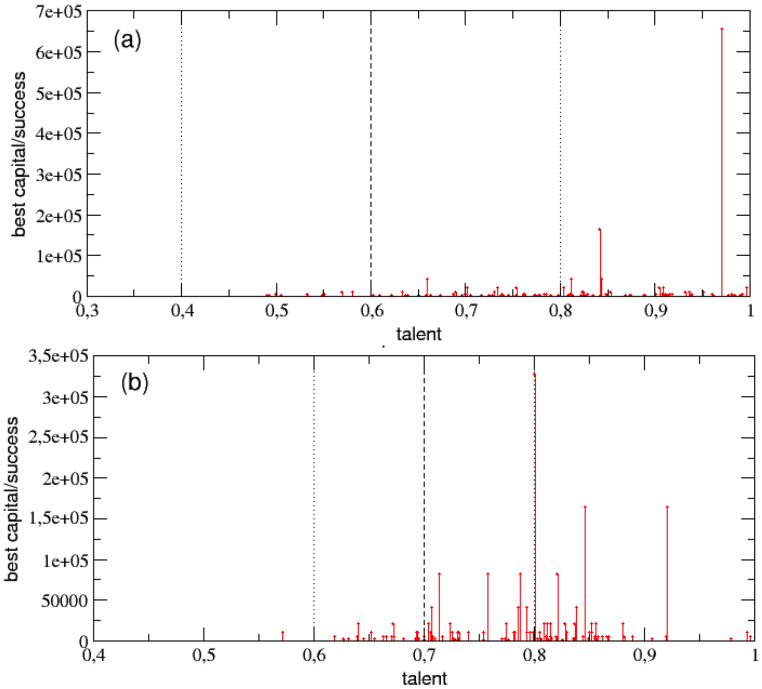

Figure 12: The final capital of the most successful individuals in each of the 100 runs is reported as function of their talent for populations with different talent distributions parameters: (a) $m_T = 0.6$ and $\sigma_T = 0.2$ (which represent a training reinforcement for the most gifted people); (b) $m_T = 0.7$ and $\sigma_T = 0.1$ (which represents an increase in the average level of education). The corresponding m_T and $m_T \pm \sigma_T$ values are also indicated as, respectively, vertical dashed and dot lines.

Actually, it results that increasing σ_T without changing m_T, as shown in panel (a), enhances the chances for more talented people to get a very high success: the best performer is, now, a very talented agent with $T = 0.97$, who reaches an incredible level of capital/success $C_{best} = 655360$. This, on one hand, could be considered positive but, on the other hand, it is an isolated case and it has, as a counterpart, an increase in the gap between unsuccessful and successful people.

Looking now at panel (b), it results that increasing m_T without changing σ_T produces a best performer, with $C_{best} = 327680$ and a talent $T = 0.8$, followed by other two with $C = 163840$ and, respectively, $T = 0.85$ and $T = 0.92$. This means that also in this case the chances for more talented people to get a very high success are enhanced, while the gap between unsuccessful and successful people is lower than before.

Finally, in both considered examples, the average value of the capital/success for the most talented people over the 100 runs is increased with respect to the value $C_{mt} \sim 63$ found in subsection 2.2. In particular, we found $C_{mt} \sim 319$ for panel (a) and $C_{mt} \sim 122$ for panel (b), but these values are quite sensitive to the specific set of simulation runs. A more reliable parameter in order to quantify the effectiveness of the social policies investigated here is, again, the indicator P_T introduced in the previous subsection, i.e. the average percentage of individuals with talent $T > m_T + \sigma_T$ and with final success/capital $C_{end} > 10$, over the total number of individuals with talent $T > m_T + \sigma_T$ (notice that now, in both the cases considered, $m_T + \sigma_T = 0.8$). In particular, we found $P_T = 38\%$ for panel (a) and $N_T = 37.5\%$ for panel (b), with a slight net

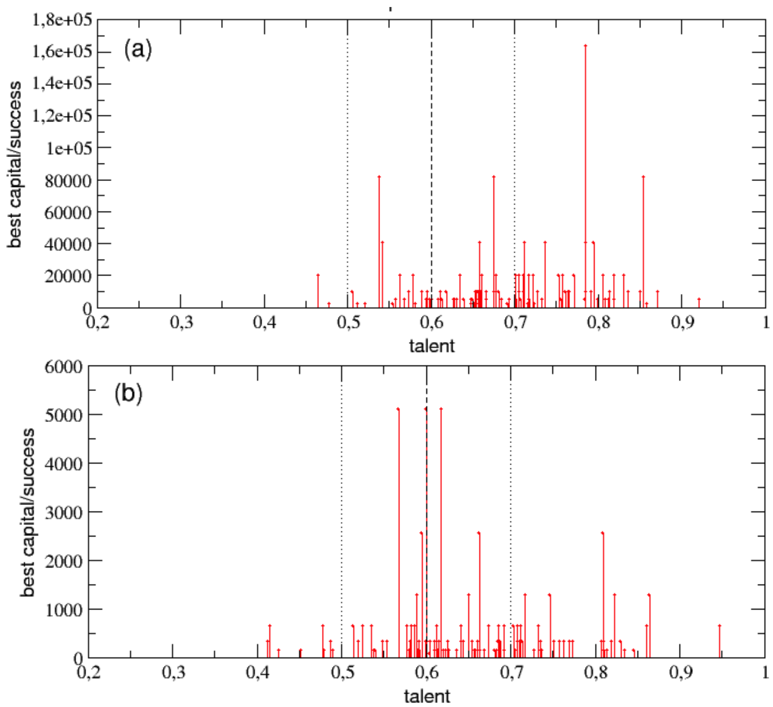

Figure 13: The final capital of the most successful individuals in each of the 100 runs is reported as function of their talent, for populations living in environments with a different percentage p_L of lucky events: (a) $p_L = 80\%$; (b) $p_L = 20\%$. The values of $m_T = 0.6$ and $m_T \pm \sigma_T$, with $\sigma_T = 0.1$ are also indicated as, respectively, vertical dashed and dot lines.

increment with respect to the reference value $P_{T0} = 32\%$ (obtained for a talent distribution with $m_T = 0.6$ and $\sigma_T = 0.1$).

Summarizing, our results indicate that to strengthen the training of the most gifted people or to increase the average level of education should produce, as one could expect, some beneficial effects on the social system, since both these policies raise the probability, for talented individuals, to grasp the opportunities that luck presents to them. On the other hand, the enhancement in the average percentage of highly talented people who are able to reach a good level of success, seems to be not particularly remarkable in both the cases analyzed, therefore the result of the corresponding educational policies appears mainly restricted to the emergence of isolated extreme successful cases.

Of course, once fixed a given level of education, it is quite obvious that the abundance of opportunities offered by the social environment, i.e. by the country where someone accidentally is born or where someone choose to live, it is another key ingredient able to influence the global performance of the system.

In Figure 13 we show results analogous to those shown in the previous figure but for other simulations, with 100 runs each and with the same parameters setup as in subsection 2.2 ($N = 1000$, $m_T = 0.6$, $\sigma_T = 0.1$, $I = 80$, $C(0) = 10$, $N_E = 500$) and with different percentages p_L of lucky events (remember that, in subsection 2.2., this percentage was set to $p_L = 50\%$). In panels (a) we set $p_L = 80\%$, in order to simulate a very stimulating environment, rich of opportunities, like that of rich and industrialized countries such as the U.S. [18]. On the other hand, in panels (b), the value $p_L = 20\%$ reproduces the case of a much less stimulating environment, with very few opportunities, like for instance that of Third World countries.

As visible in both panels, the final success/capital of the most successful individuals as function of their talent strongly depend on p_L.

When $p_L = 80\%$, as in panel (a), several agents with medium-high talent are able to reach higher levels of success compared to the case $p_L = 50\%$, with a peak of $C_{best} = 163840$. On the other hand, the average value of the capital/success for the most talented individuals, $C_{mt} \sim 149$, is quite high and, what is more important, the same holds for the indicator $P_T = 62.18\%$ (about twice with respect to the reference value $P_{T0} = 32\%$), meaning that, as expected, talented people benefits of the higher percentage of lucky events.

Completely different outcomes are obtained with $p_L = 20\%$. Indeed, as visible in panel (b), the overall level of success is now very low if compared to that found in the simulations of subsection 2.2, with a peak value C_{best} of only 5120 units: it is a footprint of a reduction in the social inequalities, which is an expected consequence of the flattening of success opportunities. According with these results, also the P_T indicator reaches a minimal value, with an average percentage of only 8.75% of talented individuals able to increase their initial level of success.

In conclusion, in this section we have shown that a stimulating environment, rich of opportunities, associated to an appropriate strategy for the distribution of funds and resources, are important factors in exploiting the potential of the most talented people, giving them more chances of success with respect to the moderately gifted, but luckier, ones. At the macro level, any policy able to influence those factors and to sustain talented individuals, will have the result of ensuring collective progress and innovation.

4 Conclusive remarks

In this paper, starting from very simple assumptions, we have presented an agent-based model which is able to quantify the role of talent and luck in the success of people's careers. The simulations show that although talent has a Gaussian distribution among agents, the resulting distribution of success/capital after a working life of 40 years, follows a power law which respects the "80-20" Pareto law for the distribution of wealth found in the real world. An important result of the simulations is that the most successful agents are almost never the most talented ones, but those around the average of the Gaussian talent distribution - another stylized fact often reported in the literature. The model shows the importance, very frequently underestimated, of lucky events in determining the final level of individual success. Since rewards and resources are usually given to those that have already reached a high level of success, mistakenly considered as a measure of competence/talent, this result is even a more harmful disincentive, causing a lack of opportunities for the most talented ones. Our results are a warning against the risks of what we call the "naive meritocracy" which, underestimating the role of randomness among the determinants of success, often fail to give honors and rewards to the most competent people. In this respect, several different scenarios have been investigated in order to discuss more efficient strategies able to counterbalance the unpredictable role of luck and give more opportunities and resources to the most talented ones - a purpose that we think should be the goal of a real meritocratic approach. Such strategies have also been shown to be the most beneficial for the entire society, since they tend to increase diversity in research and foster in this way also innovation.

Acknowlegments

A.P and A.R. would like to thank Constantino Tsallis for several discussions about the efficiency of funding strategies addressed in this paper.

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