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# The Dynamics Underlying the Rise of Star Performers

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**Abstract:** *Across different domains, there are 'star performers' who are able to generate disproportionate levels of performance output. To date, little is known about the model principles underlying the rise of star performers. Here, we propose that star performers' abilities develop according to a multi-dimensional, multiplicative and dynamical process. Based on existing literature, we defined a dynamic network model, including different parameters functioning as enhancers or inhibitors of star performance. The enhancers were multiplicity of productivity, monopolistic productivity, job autonomy, and job complexity, whereas productivity ceiling was an inhibitor. These enhancers and inhibitors were expected to influence the tail-heaviness of the performance distribution. We therefore simulated several samples of performers, thereby including the assumed enhancers and inhibitors in the dynamic networks and compared their tail-heaviness. Results showed that the dynamic network model resulted in heavier and lighter tail distributions, when including the enhancer- and inhibitor-parameters, respectively. Together, these results provide novel insights into the dynamical principles that give rise to star performers in the population.*

***Key Words:*** talent development, productivity, dynamical system, network models, simulation

## INTRODUCTION

Between 1963 and 1978 Joe Girard sold 13,001 cars for Chevrolet. He was recognized as the world's greatest salesman in the Guinness Book of World Records. In 1983, Mickey Drexler joined Gap (a worldwide clothing and accessories retailer) and turned the company into an enormous success. The sales from Gap went up from $480 million to $13.6 billion within 20 years. He earned nicknames like 'Corporate Turnaround King' and 'Merchant Prince'. In the field of sports, Wayne Gretzky has scored an incredible number of 894 goals in the National Hockey League (NHL), thereby being the top scorer of all time, who had a high impact on the successes of his teams.

The individuals mentioned above contributed a disproportionate amount to the output of their organization, they are examples of star performers (Aguinis

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& O'Boyle, 2014). Through such contributions, *star performers* can make or break the performance of an organization as a whole (Aguinis & O'Boyle, 2014). They can be found in various types of professions, related to entertainment, politics, research, sports, and more (e.g., Den Hartigh, Van Dijk, Steenbeek & Van Geert, 2016; O'Boyle & Aguinis, 2012; Simonton, 1998). To date, there is a limited understanding of star performers, and the model principles underlying the process towards their disproportionate output. An important question is therefore to understand the underlying process through which an individual ultimately becomes a star performer (e.g., Den Hartigh et al., 2016), as well as which factors may act as enhancers and inhibitors of star performance (Aguinis & O'Boyle, 2014).

## Explaining Star Performance

A long tradition of research exists on the origins of star performance, or excellent performance in a broader sense. On a group level, researchers have found some correlates like intelligence (Simonton, 2008; Simonton & Song, 2009), creativity (Simonton, 1977, 2008) and openness to experience (Feist, 1999; Hung, 2020; Simonton, 2008). At the same time, researchers have not been able to define a complete set of correlates that can explain why an individual becomes a star performer (e.g., Howe, Davidson, & Sloboda, 1998; Kaufman, 2013; Simonton, 1999). This is not surprising given some of the developmental characteristics of star performance (see Den Hartigh et al., 2016; Simonton, 2001). First, research has shown that performers develop their specific abilities at different ages. Second, the level of the domain-specific ability does not necessarily increase or decrease monotonically. Instead, a monotonic or linear road to star performance is the exception rather than the rule (for empirical demonstrations in sports and creative domains, see Gulbin, Weissensteiner, Oldenziel, & Gagné, 2013; Simonton, 2000). Third, early indicators of excellent performance are rare or even inexistent. Fourth, over the years the underlying constituents of the particular ability can change. These complexities and nonlinearities in the development of star performers are at odds with the linear models often applied in the field of psychology.

In addition to the developmental dynamics, traditional statistical models in psychology are not equipped to address a characteristic property of star performance at population level. The prevailing models that psychology researchers apply proceed from Gaussian distributions (Walberg, Strykowski, Rovai, & Hung, 1984), which hold for various human characteristics such as height, blood pressure (Pater, 2005) and intelligence (Burt, 1957). Accordingly, in industrial and organizational psychology it was long believed that individual performance displays a Gaussian distribution as well (Muchinsky, 1994; O'Boyle & Aguinis, 2012; Schmidt & Hunter, 1983). However, individuals who ultimately reach star performance find themselves in the right tail of a highly right skewed distribution (e.g., Aguinis, O'Boyle, Gonzalez-Mulé, & Joo, 2016; Aguinis & O'Boyle, 2014; Den Hartigh et al., 2016, Den Hartigh, Hill, & Van Geert, 2018; Huber, 2000; Lotka, 1926; Muchinsky, 1994; O'Boyle & Aguinis, 2012;

Simonton, 2003, 2005a; Sutter & Kocher, 2001). In other words, given that star performers produce much more output than normal individuals, they are far more on the right of the performance distribution than one would expect if individual performance would follow a Gaussian distribution. For instance, O'Boyle and Aguinis (2012) conducted five studies using 198 samples. These samples involved entertainers, politicians, researchers, and amateur and professional athletes. The authors point out that the distribution of performance follows a power law (Paretian) distribution. Their results were steady among different industries, various types of jobs, several types of performance measures and different time frames. In agreement with the research of O'Boyle and Aguinis (2012), other studies found that individual performance follows a highly right skewed and heavy tailed distribution, such as a lognormal distribution, an exponential distribution, a stretched exponential distribution or a power law distribution (Aguinis & O'Boyle, 2014; Davies, 2002; Den Hartigh et al., 2016, 2018; Deng, Li, Cai, Wang, & Bulou., 2012; Huber, 2000; Huber & Wagner-Döbler, 2001; Joo, Aguinis, & Bradley, 2017; Lotka, 1926; Muchinsky, 1994; Ruocco, Daraio, Folli, & Leonetti, 2017; Sutter & Kocher, 2001; Walberg et al., 1984). In conclusion, this means that if we translate performance into measurable performance output, like the number of sales by salesmen, number of goals scored or victories by athletes, number of published articles by scientists, star performers have an extreme right position on the distribution of performance.

The nonlinear developmental patterns of individual performers, and the highly right skewed, heavy tailed distributions of performance have consequences for the way in which we should approach and study star performance. More specifically, given that traditional additive models used in psychology result in Gaussian distributions, they do not seem suitable for modeling individual performance that typically follows a highly right skewed and heavy tailed distribution. Multiplicative dynamical network models, however, can produce these types of distributions (e.g., Den Hartigh et al., 2016, 2018; Simonton, 2001; Walberg et al., 1984; Zang, Cui, Zhu, & Wang, 2019).

## A Dynamic Network Model to Explain Star Performance

Researchers have already suggested that star performers likely develop their abilities according to multi-dimensional, multiplicative and dynamical processes (e.g., Den Hartigh et al., 2016; Marques-Quinteiro, Ramos-Villagrasa, Navarro, Passos, & Curral, 2021; Phillips, Davids, Renshaw, & Portus, 2010; Simonton, 1999, 2001, 2005b). Applying dynamic network models could provide insights into the underlying latent processes of the route to star performance (Oravecz & Vandekerckhove, 2020). Indeed, in their extensive studies on star performers across achievement domains, Aguinis and O'Boyle already hinted that a dynamic network may provide the key to understanding individual performance in organizations, and in particular the occurrence of the highly right skewed, heavy tailed performance distributions (Aguinis & O'Boyle, 2014, O'Boyle & Aguinis, 2012).

From a dynamic network perspective, the explanation for human performance does not lie in some specific (independently operating) causal factors, but rather in mutually interacting dynamic variables. In an organizational context, examples of variables that influence human performance are knowledge, skills, abilities and opportunity to produce (e.g., Merton, 1968; Schmidt & Hunter, 1998). In this article, we propose that a logistic growth dynamic network would provide better insights in the developmental trajectories of star performers. Similar models have been found to explain cognitive growth, language growth (Van Geert, 1991), child directed speech (Van Dijk et al., 2013), intelligence (Van der Maas et al., 2006), as well as different phenomena in learning and teaching (Van Geert & Steenbeek, 2005). Furthermore, Den Hartigh et al. (2016) recently demonstrated that logistic growth dynamic network models predict all the properties of human performance development mentioned in the previous section, as well as the highly right skewed, heavy tailed distribution of performance output.

A dynamic network consists of several nodes. One of the nodes reflects the ability of interest, the level of which makes it more or less likely to deliver an output (e.g., selling, scoring, publishing), and the others influence the ability via a direct or an indirect connection. Nodes can be internal variables (e.g., motivation) or external variables (e.g., organizational culture). For each pair of nodes there is a certain probability to be connected. These connections can be symmetric but also asymmetric. Moreover, they can be positively or negatively coupled. In addition, the weight of the connections differs. The nature and strength of the connections between the specific abilities and the variables is assumed to be a characteristic of that person's dynamic network (for an extensive review, see Den Hartigh et al., 2016). The values of the nodes change in time as the developmental process takes place. It is possible for nodes to disappear in time or for new nodes to appear. These changes might be a consequence of the connections between the nodes or of external changes.

## Basic Model Principles

Given the foundation described in the previous section, the development of a star performer can be expressed by a system of $n$ sparsely coupled logistic growth difference equations, where $n$ is the number of nodes. The mathematical model is based on existing models of skill development (e.g., Den Hartigh et al., 2016, 2018; Van der Maas et al., 2006; Van Geert, 1991, 1994, 2014). The mathematical equations are given by Eq. 1, where $L_1$ denotes the level of a node in the network, which might be the target ability ($L_1$) or another performance related component ($L_2$ – $L_n$). Other performance related nodes comprise all contributing factors to the level of the target node, for instance interest, motivation, but also the external factors of help and assistance the individual obtains from the environment. Hence, these nodes reflect components that are variable, shape the ability, but are not intrinsic expressions of the ability. Each of the equations shows the growth of a node over time and every individual has a different system of difference equations.

$$\begin{cases} L_1(t+1) = L_1(t) + \left(r_{L_1} L_1(t)\left(1 - \frac{L_1(t)}{K_{L_1}}\right) + \sum_{j=1}^{n} s_{1j} L_1(t) L_j(t)\right)\left(1 - \frac{L_1(t)}{C_1}\right) \\ L_2(t+1) = L_2(t) + \left(r_{L_2} L_2(t)\left(1 - \frac{L_2(t)}{K_{L_2}}\right) + \sum_{j=1}^{n} s_{2j} L_2(t) L_j(t)\right)\left(1 - \frac{L_2(t)}{C_2}\right) \\ \vdots \\ \vdots \\ L_n(t+1) = L_n(t) + \left(r_{L_n} L_n(t)\left(1 - \frac{L_n(t)}{K_{L_n}}\right) + \sum_{j=1}^{n} s_{nj} L_n(t) L_j(t)\right)\left(1 - \frac{L_n(t)}{C_n}\right) \end{cases} \tag{1}$$

Fig. 1 visualizes one system of equations. In this figure, the level of a node is indicated by the size of the circle. The level of a node is the sum of the relatively stable resources and the weighted multiplicative effect of its own level with the level of other connected performance related nodes. A relatively stable resource is more or less constant during the time window within which the node develops. For instance, a relatively stable resource of the target ability could be the genotype of an individual. The growth rate of the relatively stable resources is denoted by $r_{Li}$, which indicates the maximum amount the node can profit from the relatively stable resources. The degree to which these nodes can profit from the relatively stable resources is dependent on the carrying capacity of the stable resources, denoted by $K_{Li}$. This can be viewed as the constraints the stable resources have on the growth of the nodes. For instance, the degree to which someone's ability can profit from the genotype has its limits. Whenever the level of a specific node approaches the carrying capacity of the stable resources, $K_{Li}$, the positive effect of the stable resources on the level of the nodes decreases. When a specific node overgrows its carrying capacity of the stable resources, the node can no longer profit from the relatively stable resources. In this case, $(1 - L_i / K_{Li})$ will turn negative, changing the sign of the growth rate for the relatively stable resources.

A multiplicative effect means that the level of a node is multiplied with the level of a connected node (see Simonton, 2001). The weight of the multiplicative effect (i.e. the weight of the connections) is denoted as $s_{ij}$. These weights can either be positive, negative or be zero. They can as well be interpreted as a growth rate, that is, the amount a node profits from other connected nodes. In Fig. 1 the weight of the connections is visualized by the thickness of the arrows in between different nodes. The sign of the weight proceeding from the connection is indicated by either a solid arrow (positive connection) or a dashed arrow (negative connection).

Finally, $C_i$ is the carrying capacity of the nodes, in the sense of the ultimate limit of growth of a specific node. The carrying capacity prevents nodes reaching unrealistic values. Visually, one could think of the carrying capacity as an imaginary circle around the existing nodes in Fig. 1, preventing the nodes from growing beyond that level.

To illustrate the developmental trajectories generated by the model, Fig. 2 shows two cases generated by the dynamic network model of Eq. 1 (for parameter settings, see Methods section). Note that these figures are just two

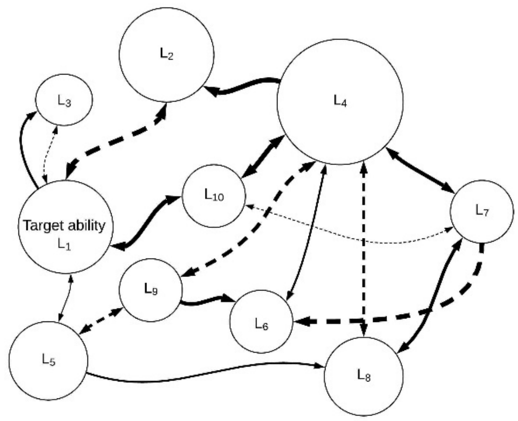


**Fig. 1.** A *dynamic network model*. Snapshot graphic example of a dynamic network model, in which the ability (target node, $L_1$) is embedded in a network of dynamically interacting other nodes ($L_2$ - $L_{10}$). The size of the nodes indicate the level of the nodes. The thickness of the arrow indicates the strength of the connection ($S_{ij}$), while a solid arrow represents a positive connection and a dashed arrow indicates a negative connection. As $r_{Li}$ and $K_{Li}$ are implicit of the level of the nodes they are not visible in this figure. The carrying capacity ($C_i$) could be envisioned as an imaginary circle around the existing nodes in this figure, preventing the nodes from growing beyond that level.

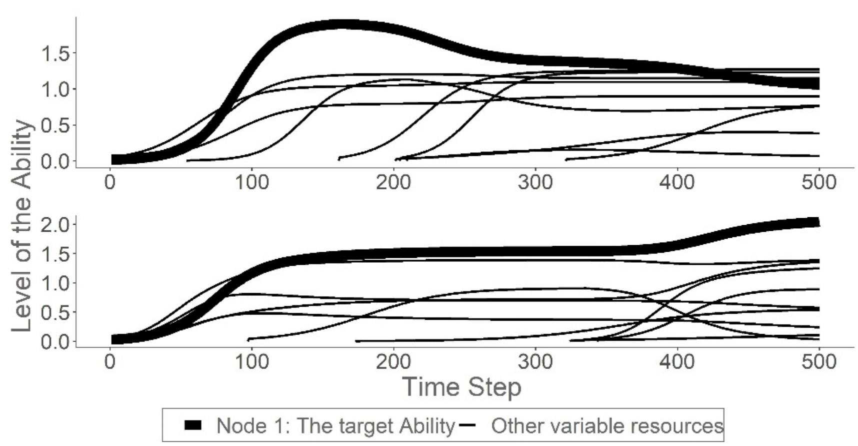


**Fig. 2.** *Developmental trajectories*. Developmental trajectories for two star performers. The different lines represent the development of the different nodes in the network. Furthermore, the bolds line shows the development of the target ability.

examples of developmental trajectories and that in line with Den Hartigh et al. (2016, 2018), the model reveals unique developmental trajectories with repeated simulations. Examining Fig. 2, one can observe that both individuals reach (star) performance levels for the ability of interest (the target node). Moreover, both graphs show that the same ability may rise at different ages, that the level of each ability does not necessarily increase or decrease monotonically, and that the same ability can be a product of different levels of other abilities. This illustrates how a dynamic network model reveals various individual developmental trajectories, which is in line with current knowledge on talent and skill development (e.g., Den Hartigh et al., 2016; Phillips et al., 2010; Simonton, 2001).

## Enhancers and Inhibitors of Star Performance

The presented dynamic network model is a basic model explaining general properties of (star) performance, and its development (Den Hartigh et al., 2016, 2018). However, literature suggests that different parameters may facilitate or hinder the development of star performers in the population. In recent work, Aguinis et al. (2016) proposed specific factors that may lead to a distribution of performance with a heavier or lighter tail, thereby containing more or less star performers, respectively. To illustrate, Fig. 3 shows the difference between a heavy and a light tailed distribution. Enhancers of the development of star performers would be multiplicity of productivity, monopolistic productivity, job autonomy and job complexity.

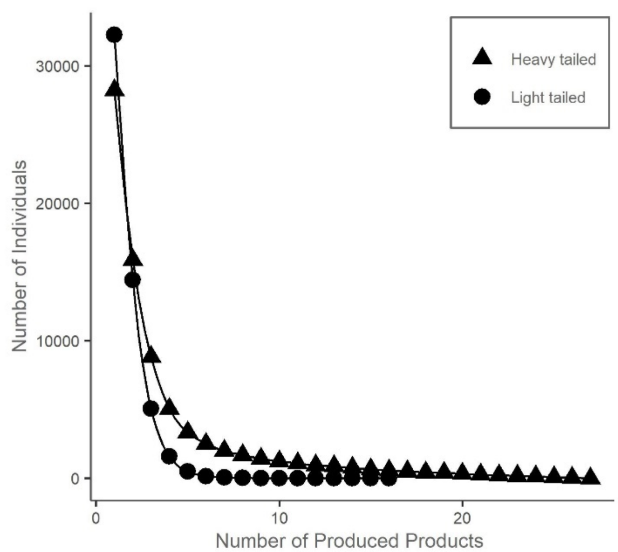


**Fig. 3.** *Heavy tailed distribution vs. light tailed distribution*. In this illustration, more star performers can be found in the tail of the heavy tailed distribution compared to the light tailed distribution.

Multiplicity of productivity, similar to the Matthew effect (Merton, 1968), is the decrease of the costs of a new output as the number of previous outputs increases. That is, in many occupations future success depends on past success, which means that it is easier for the performer to produce output as previous output increases. For example, if a researcher already published some articles in high-impact journals, it may be easier to publish again, because he or she obtained resources and has a better reputation, which are both favorable for publishing more articles (e.g., Merton, 1968; Petersen, Wang, & Stanley, 2010). According to Aguinis and colleagues (2016) the multiplicity of productivity will result in a greater proportion of star performers and therefore a heavier tail of the distribution of performance.

Monopolistic productivity is equivalent to the concept of market inequality, where a few companies have a monopoly over many others. Accordingly, star performers can also have the monopoly over other employees. Indeed, star performers are capable of dominating production by discouraging others from competing with them (Connelly, Gangloff, Tihanyi, & Crook, 2013; Sheremeta, 2016). In this scenario star performers have a higher probability of producing than their co-workers. This contributes to a heavier tail of the highly right skewed distribution of performance output (Aguinis et al., 2016).

Job autonomy is defined by how much substantial freedom, independence and discretion an individual has in his or her work schedule and in the decision making concerning the procedures to be used in carrying out the task or job (Hackman and Oldham, 1975). It is known as a factor contributing to higher job performance (Khoshnaw & Alavi, 2020; Saragih, 2017). More specifically, high autonomy offers performers the flexibility and control over processes and resources that lead to higher performance output (Kohn & Schooler, 1983). Moreover, it has a positive effect on job performance by mitigating job stress (Iseke & Muecke, 2019), increasing self-efficacy (Saragih, 2017), and increasing job commitment (Sisodia & Das, 2013). Higher autonomy in the workplace would lead to an increase in the proportion of star performers as viewed by a heavier tail in the distribution of performance (Aguinis et al., 2016).

Job complexity can be defined as a measure of the multifacetedness of the job and the degree of difficulty (Humphrey, Nahrgang, & Morgeson, 2007). Jobs that are high in complexity, involve usage of higher levels of information processing and are mentally demanding. Jobs with high complexity are known to have more variance in the number of productions (Simonton, 2001) and are therefore expected to have a heavier tailed distribution of performance (Aguinis et al., 2016; Simonton, 2001)

Finally, an inhibitor would be the productivity ceiling. This is a maximum of performance output that can be reached. For example, in a call center there is a maximum number of telephone calls, and thereby sales, one can make during an hour. As a productivity ceiling is an upper bound on the number of productions, there will be no (or less extreme) outliers, hence the distribution of performance will have a relatively lighter tail. Taken together, the enhancers and inhibitors may be thought of as relatively stable job characteristics that influence the performance of star performers. In the dynamic network model, they can be considered as parameters that are not expressed as specific nodes, but influence the settings of the network (see Methods section).

### The Current Study

Altogether, a comprehensive model of star performance in organizations should explain (a) the dynamic development of individual star performers, (b) the highly right skewed and heavy tailed distributed performance, *and* (c) the role of enhancers and inhibitors in the shape of the distribution of performance. In this study we will propose such a model by implementing the dynamic network model of human performance development presented in Eq. 1 (Den Hartigh et al., 2016, 2018), and include the enhancers and inhibitors of star performance in that model (Aguinis et al., 2016). In line with Den Hartigh and colleagues we expect that, first, the basic model would replicate a highly right skewed and heavy tailed distribution of performance output when simulating a sample of performers. Furthermore, by tuning model parameters to be reflective of enhancers and inhibitors of star performance, our model should result in a distribution of performance output with a heavier tail than the default model when increasing multiplicity of productivity, monopolistic productivity, job autonomy and job complexity. On the other hand, our model should lead to a distribution of performance with a lighter tail when including a productivity ceiling.

## METHODS

### Settings of the Dynamic Network Model

The dynamic network model given by Eq. 1 was implemented in Matlab. The basic parameter settings were set in accordance with the work by Den Hartigh et al. (2016, 2018). A set of 10 nodes was specified, and we simulated the trajectories of performers in 500 time-steps. Each pair of nodes was connected with a probability of 25%. The strength of these connections was drawn from a Gaussian distribution and differed for each pair of nodes and for each individual. Nodes were not able to connect with themselves. Not all nodes emerged at the same time step or started at the same level. For the first four nodes the time of initial emergence was zero, while for the rest of the nodes the time of initial emergence was drawn from a uniform distribution for each individual. The initial level of each node was drawn from a Gaussian distribution for each node and each individual. Finally, the carrying capacity of the relatively stable resources, the growth rate for the relatively stable resources and the carrying capacity for the nodes had different values for each node and for each individual.

We simulated 100,000 individuals, and for all these individuals a new set of parameters was drawn from a Gaussian or uniform distribution of values (Table 1). As most datasets in performance research contain only individuals that produce one or more outputs (e.g., Aguinis et al., 2016), we decided to only consider these individuals. Hence, even though we simulated 100,000 individuals not all these individuals were included in the analysis. We chose the first node as the target (ability) variable.

**Table 1.** Parameter settings. Default parameter values used for the dynamic model simulations.

| *Parameter (drawn from a Gaussian distribution)* | *Mean* | *SD* |
|---|---|---|
| r (growth rate for the relatively stable resources) | 0.05 | 0.01 |
| K (carrying capacity of the stable resources) | 1.00 | 0.15 |
| s (connection strengths with nodes) | 0.00 | 0.02 |
| Probability of connections | 0.25 | 0.00 |
| *Parameter (drawn from a uniform distribution)* | *Min* | *Max* |
| L (initial level of the nodes) | 0.00 | 0.05 |
| C (carrying capacity of the nodes) | 10.00 | 25.00 |
| T (time of initial emergence) | 1.00 | 350.00 |

Source: Den Hartigh et al. 2016, 2018.

## Modeling Performance Output

In order to examine the simulated distribution of performance, we transformed the level of the target variable (the ability; $L_1$) to a probability of production at different time steps for different individuals. In line with Den Hartigh et al. (2016) we used a probabilistic model in which the probability that a particular output was produced at a certain time step was a function of the level of the target variable (the ability; $L_1$) and a domain-specific parameter ($\phi$), which we called the production parameter (cf. Den Hartigh, 2016; Simonton, 2003). At every time step there was a relatively small probability that an output (selling, scoring, publishing) was produced. This probability was relatively higher for individuals with higher ability levels. In this study we set $\phi = 1 / T$, where $T$ is the number of timesteps (i.e., 500). The probability that an output $p$ was produced at timestep $t$ is given by Eq. 2.

$$P(p_t) = \phi\, L_1(t). \tag{2}$$

In the case that $P(p_t) \geq 1$, we took $P(p_t) = 1$. We implemented this model in Matlab. An individual produced at time step $t$, if a random number between zero and one was smaller than the probability to produce. The total number of produced outputs was saved for each individual.

### Testing the Distribution of Performance Output

To examine if the simulations of the dynamic model without the influence of the enhancers or inhibitors (i.e., the default distribution) lead to a highly right skewed distribution of performance, we simulated 100,000 individuals. We visualized this distribution and created a Cullen and Frey graph with 1,000 bootstrap samples to assess the shape of the distribution. Subsequently, we fitted a Gaussian, exponential, Pareto, lognormal, gamma, Poisson and Weibull distribution to the simulated distribution of performance using maximum likelihood estimation. For all of the fitted distributions, we calculated and compared the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). We selected the distribution with the minimal AIC and BIC as the distribution of performance. For this distribution we created a quantile-quantile plot (q-q plot) and visually explored the fit of the distribution. Finally, to confirm that our simulated data fulfills a power relationship we also plotted the simulated distribution of performance in a log-log plot.

### Modeling the Enhancers and Inhibitors

To include the influence of the enhancers and inhibitors on the simulated distribution of performance, we translated them into parameter adjustments of the basic model. Multiplicity of productivity was modeled using a Matthew model (Den Hartigh et al., 2016; DiPrete & Eirich, 2006; Merton, 1968; Petersen, Jung, Yang, & Stanley, 2011). The Matthew model calculates the probability that an individual produces at time step $t$ by taking, next to the level of the ability ($L_1$) and the production parameter ($\phi$), the previous production of that individual into account. The Matthew model is given by Eq. 3, where $\gamma$ is a scaling factor and $S(t)$ is the number of outputs that are already produced at time step $t$ by this individual. If we assume that $\gamma > 0$, the probability of a next production increases with the number of outputs. Hence, the Mathew model is suitable to model a sample with multiplicity of productivity.

$$P(p_t) = \phi \, L_1(t) \, (1 + \gamma S(t)). \tag{3}$$

In our simulations we used $\gamma = 25 / T$. This means that in our study every time an individual produced one product, their production parameter grew with 5%.

In a sample with monopolistic productivity star performers have a higher probability to produce than their co-workers. In our model this corresponds to doubling the production parameter $\phi$ for each individual after they produced more than two products. This specific number of two products was chosen, because only 7.5% of the performers produced more than two products. This gives star performers the monopoly of production over others.

Increasing job autonomy has a positive influence on nodes (e.g., positive effects on self-efficacy and job commitment). Furthermore, it mitigates the negative effects of other nodes like job stress. Higher job autonomy is therefore equivalent to increasing the weight ($s_{ij}$) of the connected nodes that have a positive effect and decreasing the weight of them that have a negative effect. Therefore, to simulate the effects of job autonomy the weight of the positive connections was doubled and halved for negative connections.

Professions that are higher in complexity require usage of higher levels of information processing and are mentally more demanding (Humphrey, Nahrgang, & Morgeson, 2007). These higher levels of information processing give individuals the opportunity to profit more from their stable resources (e.g. intelligence). In our model this is equivalent to increasing the carrying capacity of the relatively stable resources. This leads to more variance in the number of productions, which is typical for professions that are high in complexity (Simonton, 2001). Therefore, we doubled the mean of the carrying capacity from the relatively stable resources (i.e. mean of $K_L = 2.0$).

To simulate a productivity ceiling, we implemented that after the productivity ceiling is reached, the probabilities to produce equals zero. Hence, after an individual reached the productivity ceiling of the target variable, nothing more would be produced. We used a productivity ceiling of six products.

Having defined the model with enhancers and inhibitors, the next step would be to have a closer look at the distributions of performance simulated by the model.

## Methods for Comparisons of Distributions with Enhancers and Inhibitors

To confirm that our model was in agreement with the literature we compared the tail of the simulated default distribution to the tail of the simulated distributions of performance with the enhancers and inhibitors visually as well as numerically. One method to check the differences in the tailedness of two distributions numerically would be to look at their kurtosis. However, since kurtosis is not normally distributed it is not suitable for comparisons using a statistical test. Therefore, we implemented a method to make inferences about the changes in the heaviness of the tail of the distribution of performance. We specifically used L-moments for this, which is explained in the next section.

### L-moments to Make Inferences About the Distribution of Performance

L-moments are analogous to conventional moments of probability distributions. They are defined as a linear combination of order statistics and were introduced by Hosking in 1990 (Hosking, 1990). Since their introduction they are widely used in different fields of research, more specifically in hydrology, climatology, meteorology, economics and socio-economics (Bastianin, 2020; Eslamian & Feizi, 2007; Hosking & Wallis, 1993; Karvanen, 2006; Lee & Maeng, 2005; Śimková, 2017; Bílková, 2014).

Similar to conventional moments, L-moments can be used as a measure of distributional shape. More specifically, $\lambda_1$ is the mean of the distribution, $\lambda_2$ is a measure of dispersion of the distribution, $\lambda_3$ can be interpreted as a measure of skewness of the distribution and $\lambda_4$ can be interpreted as a measure of kurtosis of the distribution (Hosking, 1990). For the exact definition of L-moments we refer to the original paper by Hosking (1990). The values for $\lambda_3$ and $\lambda_4$ depend on the scale of the distribution. Therefore, we introduce L-moments ratios: $\tau_r = \lambda_r / \lambda_2$, for $r$ = 3, 4, ... The third and fourth L-moment ratios are dimensionless measures of respectively skewness and kurtosis. We will refer to them as L-skewness and L-kurtosis.

There are several advantages of L-moments over conventional moments. First, they are more easily interpretable as measures of distributional shape (Hosking & Wallis, 1993). Moreover, unlike the conventional skewness and kurtosis measure, the L-moment ratios, L-skewness and L-kurtosis, are asymptotically normally distributed (Hosking, 1990). This makes it possible to perform statistical comparisons on the L-skewness and L-kurtosis of different distributions. Finally, L-moments are unique for a distribution; are more robust for extreme values; and all their orders exist under the assumption that the mean is finite (Hosking, 1990; Śimková, 2017). Altogether, this makes them very suited for modeling rare events like star performance.

### Testing the Influence of the Enhancers and Inhibitors

To examine if our model behaved in accordance with our expectations we tested if the enhancers and inhibitors indeed lead to a simulated distribution of performance with heavier and lighter tails, respectively. We simulated samples containing 100,000 individuals for each enhancer or inhibitor. We first visually compared the differences in the tail-heaviness of the default distribution with the distributions of the enhancers and inhibitors. Then, to test the differences in tail-heaviness, we drew 1,000 bootstrap samples and computed the L-kurtosis for each of these bootstrapped samples and performed a t-test.

To examine the robustness of the dynamical network model and the tuning of the enhancers and inhibitors we performed aforementioned analyses with different numbers of nodes and different numbers of individuals. More specifically, we performed the analyses for 25 and 50 nodes, while keeping the number of simulated individuals constant. Furthermore, using a network of 10 nodes we simulated 10,000, 50,000 and 1,000,000 individuals for each enhancer/inhibitor and performed aforementioned analyses.

## RESULTS

### The Distribution of Performance Output

One sample of performers was simulated with the default settings (see Table 1). Note that even though we simulated 100,000 individuals, we only analyzed the individuals that produced (i.e., 54,318 individuals). The distribution of performance, the Cullen and Frey diagram, and the log-log plot can be found in Fig. 4(a), (b) and (c). The Cullen and Frey diagram shows clearly that it is unlikely that the performance outputs of the model simulations follow a normal distribution. It shows that the distribution of performance is much more skewed and has much more kurtosis. According to the Cullen and Frey graph a possible candidate for this distribution is a lognormal distribution. The log-log plot of the distribution of performance shows that our simulated data fulfills a power relationship. This power relationship seems to be even stronger in the tail of the distribution, which is in accordance with the extensive research into the fit of several performance databases of Aguinis et al. (2016).

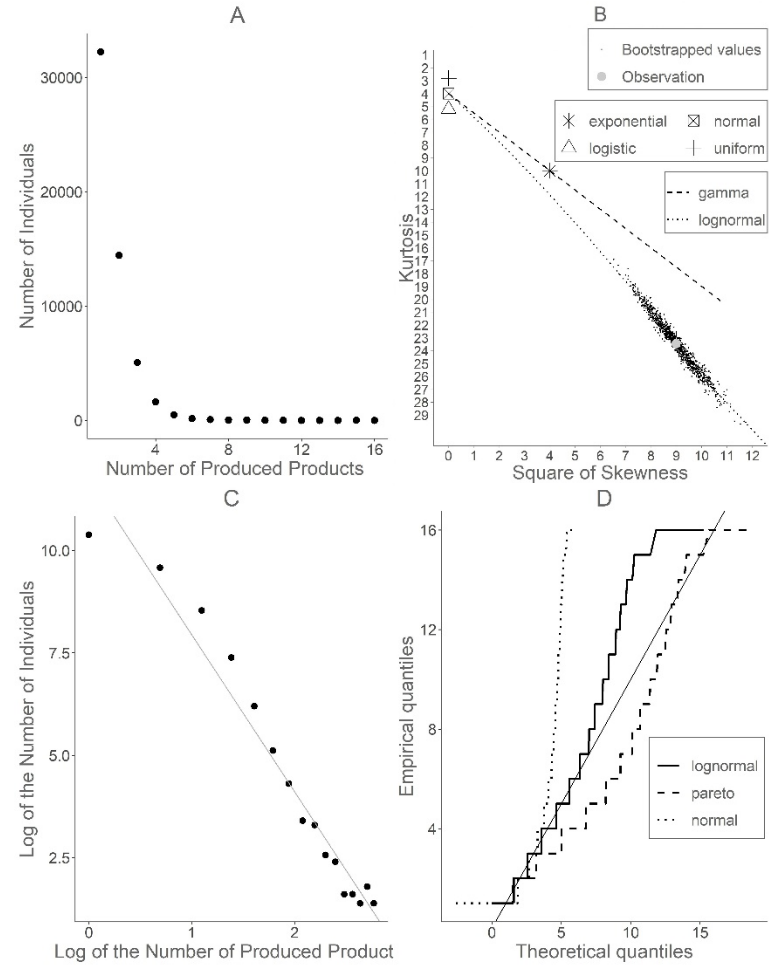


**Fig. 4.** *Distribution of performance for the default distribution*. Figure (a) shows the distribution of performance for the default sample for 54,204 individuals. Figure (b) represents the Cullen and Frey diagram for a simulated default sample, with 1,000 bootstrap samples. Figure (c) shows the log-log plot for the default sample. It follows a straight line, indicating that the distribution of performance fulfils a power relationship. This relationship seems to be even stronger in the tail of the distribution. Figure (d) depicts the q-q plot for a fitted normal distribution, Pareto distribution and a lognormal distribution.

Next, we calculated the AIC and BIC of several distributions (see Table 2). Both criteria indicate that the lognormal distribution has the best fit. Subsequently we visually checked the fit of the lognormal distribution with the simulated distribution of performance using a q-q plot (see Fig. 4(d)). The q-q plot shows that the distribution of performance is well fitted by a lognormal distribution in the beginning. However, the tail of the distribution of performance seems to be more heavy tailed and better fitted by for example the tail of a Pareto distribution. Hence, the distribution of performance is highly right skewed and heavy tailed. Therefore, in accordance with Den Hartigh et al. (2016), we can confirm that a dynamic network model generally results in a highly right skewed and heavy tailed distribution of performance.

**Table 2.** *Fitted Distributions*. AIC and BIC for the Fitted Distributions.

| *Fitted distribution* | *AIC* | *BIC* |
|---|---|---|
| Lognormal distribution | 113,563.7 | 113581.5 |
| Gamma distribution | 120,236.7 | 120254.5 |
| Weibull distribution | 132,060.7 | 132078.5 |
| Poisson distribution | 150,772.9 | 150781.8 |
| Gaussian distribution | 152,063.7 | 152081.5 |
| Exponential distribution | 160,712.0 | 160720.9 |
| Pareto distribution | 160,718.0 | 160735.8 |

## The Effects of Enhancers and Inhibitors

We generated a sample of 100,000 individuals for each of the modeled enhancers or inhibitors and visually compared the distribution of performance with the default distribution. Fig. 5(a) reveals a heavier tail for the sample with multiplicity of productivity. More individuals seem to produce a disproportionate amount of output. In addition, the output appears to be more extreme. Therefore, this plot shows that including multiplicity of productivity in the model simulations leads to more star performers.

Furthermore Fig. 5(b) reveals more star performers as well as more extreme results for the sample with monopolistic productivity compared to the default sample. Hence, this result confirms that including monopolistic productivity in the model leads to a heavier tailed distribution of performance output.

Fig. 5(c) shows that the total amount of outputs is much higher for the sample with high autonomy compared to the default sample. We can conclude that the total amount of star performers is much higher when job autonomy is increased in the model. This implies that including job autonomy in the model enhances the heaviness of the tail of the highly right skewed distribution of performance output.

Fig. 5(d) shows that the sample with higher job complexity has considerably more star performers. This is in accordance with the idea that job complexity enhances the heaviness of the tail of the distribution of performance output.

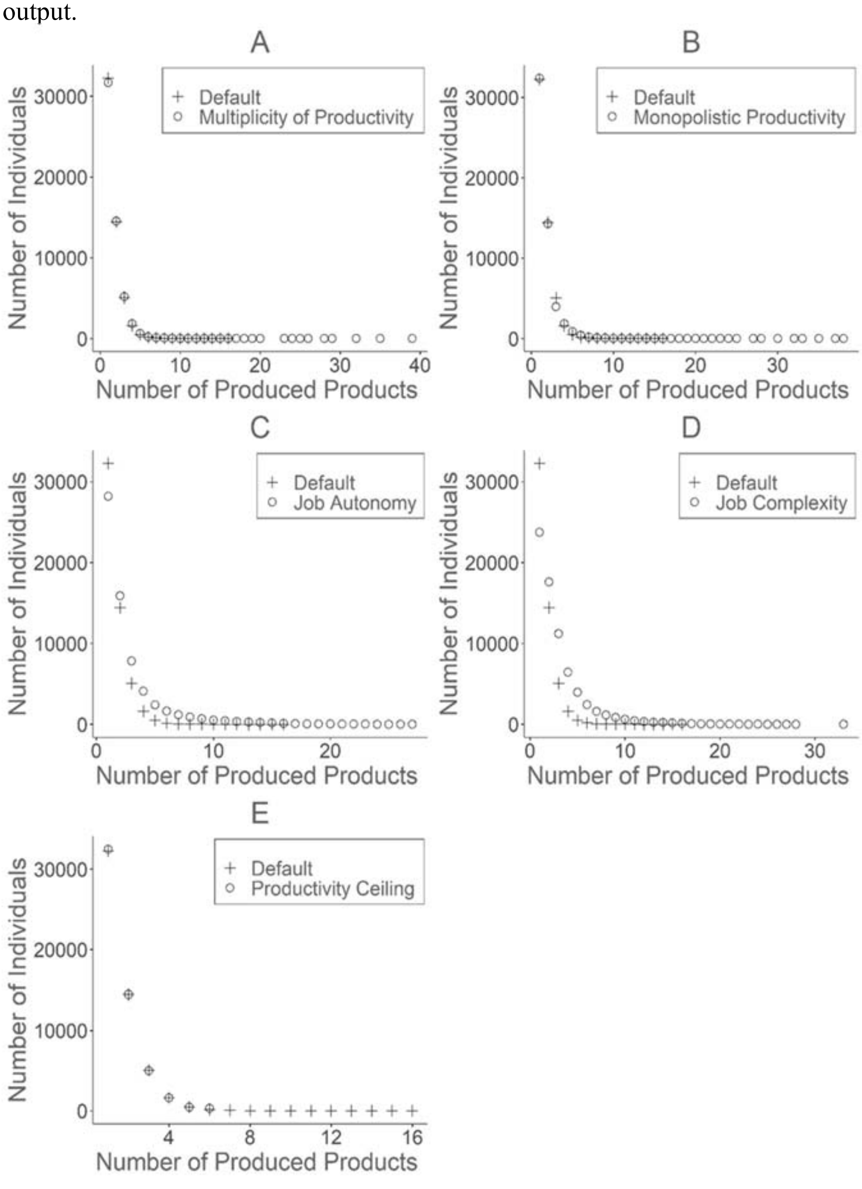


**Fig. 5.** *Distribution of performance for the enhancers and inhibitors*. Distribution of performance for a default sample indicated by + and distribution of performance for the enhancers (a)-(d) and inhibitors (e) indicated by o. Note that the

distributions of performance of the enhancers and inhibitors have a heavier tail and a lighter tail, respectively.

Finally, Fig. 5(e) reveals a lighter tail for the sample with a productivity ceiling compared to the default sample. Therefore, our results confirm that including a productivity ceiling in the model leads to a distribution of performance with a lighter tail.

Then, to test the differences in tail-heaviness we drew 1,000 bootstrap samples. The L-kurtosis was calculated for each of these bootstrapped samples. Descriptive statistics of the L-kurtosis values can be found in Table 3. To confirm that including the proposed enhancers and inhibitors in our model results in a distribution of performance with a heavier or lighter tail than the default sample, respectively, we performed t-tests between the L-kurtosis values of the samples including the enhancers or inhibitors and the samples generated with the default settings. All t-tests resulted in a significant difference ($p < .001$) in the expected direction (see Table 3).

**Table 3.** Descriptive Statistics of the L-kurtosis, and Results of the t-Tests Between the L-kurtosis of the Default Distribution and the Distribution with Enhancers and Inhibitors.

| *Sample* | *N* | *Mean L-kurtosis* | *SD* | *DF* | *t-statistic* |
|---|---|---|---|---|---|
| Default | 54,204 | 0.143 | 0.003 | NA | NA |
| Multiplicity of productivity | 54,402 | 0.164 | 0.004 | 1817.3 | 125.4*** |
| Monopolistic productivity | 54,294 | 0.235 | 0.004 | 1808.5 | 543.7*** |
| Job autonomy | 65,264 | 0.265 | 0.002 | 1747.9 | 1030.5*** |
| Job complexity | 71,465 | 0.212 | 0.002 | 1670.2 | 597.5*** |
| Productivity ceiling | 54,325 | 0.124 | 0.002 | 1824.2 | -153.2*** |

*** $p < .001$

## Robustness

As a robustness check we confirmed the effects of the enhancers and inhibitors on the simulated distribution of performance for different sample- and network sizes. Both networks of 25 and 50 nodes gave similar results, that is, the tail of the distribution was visually clearly heavier for all the enhancers and lighter for the inhibitors. Moreover, including enhancers in the models led to a distribution with a significantly heavier tail (all $p < 0.001$) and including the inhibitor led to a distribution with a significantly lighter tail ($p < 0.001$).

Finally, we simulated 10,000, 50,000 and 1,000,000 individuals for each enhancer/inhibitor. We found that, for different numbers of individuals, the result were again similar. Including enhancers in the models led to a distribution with a significantly heavier tail ($p < 0.001$) and including the inhibitor led to a distribution with a significantly lighter tail ($p < 0.001$). Hence, we can conclude that the effects of the enhancers and inhibitors seem to be robust for different network- and sample sizes.

## DISCUSSION

For over a century, researchers have been looking for an explanation of the emergence of star performers. Although the dominant search for an explanation or theoretical model lies in the use of additive models, in this research we used a dynamic network model, thereby proceeding from the theory of nonlinear dynamical systems. An important new step of our research was to extend the dynamic network model by including enhancers and inhibitors of star performance in organizations. We found that all modeled enhancers and inhibitors changed the tail-heaviness of the distribution of performance significantly. Although this could be expected based on previous work (Aguinis et al., 2016), this paper is the first to implement such enhancers and inhibitors in a dynamic network model underlying the rise of star performers.

It could be noted that the model principles we presented are simplifications of the real world. However, from a model building perspective, it is important to first study the simplest model possible that can generate typical properties of the phenomenon of interest. In our case, we therefore implemented the enhancers and inhibitors by tuning parameters of the default model, in a way that makes sense in light of previous work (Aguinis et al., 2016). Furthermore, the model is fairly theoretical, that is, while it is possible to get better insight into the developmental paths of star performance it is not (yet) possible to use this model to predict the performance output of employees. For example, it would be interesting to explore if a model can be created that predicts if a particular individual will become a star performer or not. Modeling predictions of these forms can help managers to predict personnel's capabilities and to recruit appropriate new personnel with relevant skills. This can significantly enhance an enterprise's competitiveness in the market (Li, Kong, Ma, Gong, & Huai, 2016). For instance, in case one could acquire longitudinal data from a certain performance area it would be interesting to fit a dynamical network model to this data to explore the latent processes in the rise of star performers (Oravecz & Vandekerckhove, 2020).

In light of the above, machine learning or neural networks may also be employed in future work. Li and colleagues (2016) already showed that prediction of human performance can be done using a k nearest neighbor algorithm. A next step could be to use more advanced algorithms like random forest, or even a recurrent neural network in the case of longitudinal data (e.g., Long Short-Term

Memory). These kinds of algorithms have recently been explored in psychological research and health sciences, and first results are promising (Lipton, Kale, Elkan, & Wetzel, 2015; Rahman, & Adjeroh, 2019; Stewart, Sprivulis, & Dwivedi, 2018; Strobl, Malley, & Tutz, 2009; Tang, Xiao, Wang, & Zhou, 2018; Wijnands, Thompson, Aschwanden, & Stevenson, 2018). Another interesting approach would be to find new features of an individual's personal network that have an influence on the distribution of performance (Aguinis et al., 2016). For example, Morrison (2002) showed that new employees with larger informational personal networks throughout multiple organizational units have greater knowledge of the organization, while employees with denser and stronger personal network experienced greater mastery of their jobs and more role clarity. This difference may also be visible in the distribution of performance. Furthermore, varying other parameters like the probability of a connection, the number of negative or positive connections, or the strength of all connections may affect the distribution of performance. These kinds of experimentations with our model may further increase our understanding of the theoretical mechanisms behind the development of star performance.

## CONCLUSION

The dynamic network model that we proposed generates simulations of the route to star performance that are close to the existing literature (e.g., Den Hartigh et al., 2016). The model gave rise to a heavy tailed distribution of performance. In addition, and in accordance with the literature (Aguinis et al., 2016), varying the enhancers and inhibitors influenced the heaviness of the tail of this distribution significantly. Hence, we described the rise of star performers in organizations mathematically, by embedding the enhancers and inhibitors in our model. Referring back to the initial cases of star performance, although star performance may develop in various ways, Joe Girard, Mickey Drexler and Wayne Gretzky might have benefited from productivity enhancers or the lack of productivity inhibitors in their organizations. To give an example based on data from a website about Joe Girard (www.JoeGirard.com), he had the autonomy to hire individuals to help out with several business processes and business growth. During the last years of Joe Girard's working life, he arranged his job in such a way that by the time he met a potential customer he already knew everything he needed to know about the customer. Hence, because he outsourced several activities, he had the opportunity to focus fully on selling cars and therefore his productivity ceiling (e.g., the maximum number of cars that one can sell in a timespan) was much higher than for other retailers.

Finally, given our results, and new developments in the domains of dynamical systems modeling and machine learning (see previous section), the field of nonlinear dynamical systems has much to offer to improve our understanding of star performance. Further research into (dynamically) modeling the developmental path of a star performer may eventually help potential star performers to flourish, which is the key to organizational success.

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