DIW BERLIN

1763

Discussion Papers

Deutsches Institut für Wirtschaftsforschung 2018

Prediction Based on Entrepreneurship-Prone Personality Profiles: Sometimes Worse Than the Toss of a Coin

Alexander Konon and Alexander Kritikos

IMPRESSUM

DIW Berlin
German Institute for Economic Research
Mohrenstr. 58
10117 Berlin

Tel. +49 (30) 897 89-0
Fax +49 (30) 897 89-200
http://www.diw.de

ISSN electronic edition 1619-4535

Papers can be downloaded free of charge from the DIW Berlin website:
http://www.diw.de/discussionpapers

Discussion Papers of DIW Berlin are indexed in RePEc and SSRN:
http://ideas.repec.org/s/diw/diwwpp.html
http://www.ssrn.com/link/DIW-Berlin-German-Inst-Econ-Res.html

Prediction based on entrepreneurship-prone personality profiles: Sometimes worse than the toss of a coin[a]

Alexander Konon[b], Alexander Kritikos[c]

This version: October, 2018

The human personality predicts a wide range of activities and occupational choices—from musical sophistication to entrepreneurial careers. However, which method should be applied if information on personality traits is used for prediction and advice? In psychological research, group profiles are widely employed. In this contribution, we examine the performance of profiles using the example of career prediction and advice, involving a comparison of average trait scores of successful entrepreneurs with the traits of potential entrepreneurs. Based on a simple theoretical model estimated with GSOEP data and analyzed with Monte Carlo methods, we show, for the first time, that the choice of the comparison method matters substantially. We reveal that under certain conditions the performance of average profiles is inferior to the tossing of a coin. Alternative methods, such as directly estimating success probabilities, deliver better performance and are more robust.

JEL classification: C15, D81, L26

Keywords: Advice, personality, entrepreneurship, profiles

[a]We are indebted to the participants of the Entrepreneurship Residence Week, in particular Moren Levesque, Simon Parker, and Mirjam van Praag, for comments that helped us to improve this paper.

[b]Alexander Konon is Research Associate at the German Institute for Economic Research (DIW Berlin), e-mail: akonon@diw.de.

[c]Alexander Kritikos (corresponding author) is Research Director at the German Institute for Economic Research (DIW Berlin), Professor of Economics at the University of Potsdam, and Research Fellow of the IZA, Bonn and of the IAB, Nuremberg, e-mail: akritikos@diw.de.

1 Motivation

> Based on the comparison with personality profiles of top-entrepreneurs, I selected six out of 1,500 applicants and decided to heavily invest into their entrepreneurial ideas. *(The CEO of an American investment company, Nov. 2016)*

Personality predicts a wide range of human activities and occupational choices, including cadet performance (Mayer & Skimmyhorn 2017), musical sophistication (Green, Müllensiefen, Lamb & Rentfrow 2015), migration (Jokela 2009), human values (Fischer & Boer 2014), job satisfaction (Heller, Ferris, Brown & Watson 2009), and conflict in interpersonal relations (Bono, Boles, Judge & Lauver 2002). The personality is also an essential determinant of occupational choices in general (Holland 1997; Heckman, Stixrud & Urzua 2006; Borghans, Duckworth, Heckman & ter Weel 2008) and matters when individuals decide to venture a business, seeking to maintain it successfully (Zhao & Seibert 2006; Rauch & Frese 2007; Caliendo, Fossen & Kritikos 2014). Personality traits are also a predictor of entrepreneurial income (Levine & Rubinstein 2017; Manso 2016). Several researchers argue that entrepreneurs may fail even when they have a convincing idea, access to finance, and possess high education but not the "necessary" personality traits (Kalleberg & Leicht 1991; Shaver & Scott 1991) to successfully run an own business.

Thus, career outcomes are influenced by personality. For instance, it seems that individuals with a certain personality are better able to become successful entrepreneurs than others, leading to the main question addressed in this paper: Are observations on personality traits of successful entrepreneurs useful for prediction and advice? More specifically, which method should be used when processing information on successful entrepreneurs and make this information available to create a helpful advice on whether to start or not to start a business?

There is a rich literature analyzing which traits are important for an entrepreneurial career. A larger part of research in this field (e.g., Begley & Boyd 1987; Stewart & Roth 2001; Zhao & Seibert 2006; Rauch & Frese 2007) uses a simple routine and compares the average score of personality traits of successful entrepreneurs with the average trait scores of others, for instance, managers, individuals in wage employment, or unsuccessful entrepreneurs. Based on differences in average trait scores in inventories such as the Big Five an indicator profile of a successful entrepreneur is then created. We refer to this method as the *average-scores* approach.

We test whether information generated by this commonly used method is a robust predictor. In order to do so, we analyze whether advice should be given to potential entrepreneurs based on a comparison of the individual scores of these candidates with the average metric, capturing information about the entrepreneurship-prone personality profile of the prototype of an successful entrepreneur (Zhao & Seibert 2006; Rauch & Frese 2007; Obschonka, Silbereisen & Schmitt-Rodermund 2010). In other words: We test whether this commonly used method is helpful to derive recommendations and advice for future careers choices.

This question has become increasingly important, as entrepreneurial entry decisions are influenced by others' advice (Bosma, Hessels, Schutjens, Van Praag & Verheul 2012). Moreover, in many countries, there is a huge consulting industry offering personality checks to individuals who plan to become entrepreneurs.[1] Products range from online questionnaires (some of them free of charge) to offline offers by chambers of commerce, psychologists, consultants, coaches, mentors, trainers, teachers, and other practitioners. Some charge substantial fees for their advice, while suggesting to compare the individual personality scores of a candidate to the average personality scores of successful entrepreneurs (Caliendo, Kritikos, Künn, Loersch, Schröder & Schütz 2014). Similarly, banks and investors are periodically tempted to implement personality inventories as part of their decision process of whether individuals should get loans or equity for their start-ups. They often aim to apply deterministic thresholds levels where individuals would get access to capital only if the evaluation of their personality reveals a score above a benchmark (see the introductory quote, but also Rodionova 2015).

The benefits of a helpful prediction or advice would be numerous. If proper advice is provided, individuals would make better occupational choices; those who are not suited to become entrepreneurs would avoid costly misallocations; and those who are suited to become entrepreneurs would be encouraged to do so. Banks would avoid credit defaults, investors avoid losses, and consumers would largely benefit from entrepreneurial entries creating better or cheaper products. Proper advice for or against entrepreneurship would also greatly

[1] Similar approaches, as discussed here, are also used to provide advice, for instance, to young adolescent individuals seeking guidance on occupational choice.

benefit society in general, as half of nascent entrepreneurs fail in the first five years (Helmers & Rogers 2010; Quatraro & Vivarelli 2015). Economic and psychological costs generated by entrepreneurial failure, like the loss of the own savings, over-indebtedness, or unemployment in the aftermath of failure, could be reduced, if individuals being unfit for entrepreneurship are correctly advised to remain or become paid employees. In addition, decisions based on wrong advice bear substantial cost to the wrongly advised individuals and also lead to welfare losses for the society. This holds true not only for individuals who are advised to become entrepreneurs but should not, but also for individuals able to become an entrepreneur who are advised not to start an entrepreneurial career.

Therefore, to understand whether such an advice is indeed able to achieve its main goal—encouraging individuals with entrepreneurship-prone personalities to start an own business and discouraging those who do not have such a personality—the first step in making recommendations work is to make sure that the used method is helpful when processing career advice for potential entrepreneurs. Although widely applied, to the best of our knowledge, no study has analyzed whether a profile based on average-scores or an alternative method produce valuable predictions, allowing to give proper advice on whether or not to become an entrepreneur.

We close this gap by approaching this problem in the following way. In the first step, we propose a conceptual framework allowing us to judge whether a method is able to achieve its main goal, namely to induce better occupational choices. For this reason, we develop a simple recommendation problem where giving an advice on whether to start or not to start a business, is based on a personality profile correlated with entrepreneurial abilities. We rely on previous research showing that entrepreneurial abilities are an important prerequisite of becoming successful as an entrepreneur (see, *inter alia*, Holmes & Schmitz 1990). Previous research also demonstrated that there is great variance in these abilities (Astebro & Chen 2014); that nascent entrepreneurs have incomplete information about their abilities (Bernardo & Welch 2001; Koellinger, Minniti & Schade 2007; Kerr, Nanda & Rhodes-Kropf 2014); and that entrepreneurial abilities are at the same time positively correlated with personality traits (for recent results, see Caliendo et al. 2014; Levine & Rubinstein 2017; Manso 2016).

Based on our conceptual framework, we then conduct, in a second step, a number of recommendation experiments using Monte Carlo methods. We estimate the parameters of our data generating process with data from the German

Socio-economic Panel. In such a way, the Monte Carlo experiment is performed under realistic conditions. In addition, we check the robustness of our results by applying a multitude of different parameter combinations. Using the case of recommendations for or against an entrepreneurial career, we demonstrate that the common approach of taking advantage of entrepreneurship-prone personality profiles to predict career outcomes lacks robustness and results in a weak performance, which can be outperformed by a simple coin.

The remainder of the paper is organized as follows. In Section 2 we briefly review the related literature on what we know about the personality traits of entrepreneurs and more importantly on the method of deriving an entrepreneurship-prone personality profile. We, then, present our conceptual framework in Section 3. Section 4 provides an implementation of the average-scores approach. In Section 5, we analyze and compare performance in different situations. Section 6 concludes.

2 Previous research

Empirical evidence shows that personality traits are relevant for entrepreneurial choice and success. The personality structure of entrepreneurs is distinct from that of managers and workers, when measured either by the multidimensional approach of the Big Five personality construct (Zhao & Seibert 2006) or by a specific set of personality characteristics (Rauch & Frese 2007).[2]

The Big Five model consists of five distinct traits: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Based on a large number of cross-sectional studies comparing the traits of active entrepreneurs with other individuals, the meta analysis of Zhao & Seibert (2006) shows that entrepreneurs score higher on Conscientiousness and Openness to Experience, and lower on Neuroticism and Agreeableness. They found no difference for Extraversion. In an another meta analysis (see Zhao, Seibert & Lumpkin 2010) they do so, and others also find differences between entrepreneurs and other individuals with respect to Extraversion (see e.g. Caliendo et al. 2014). Furthermore, risk attitudes are also a prominent personality trait being highly relevant for entrepreneurial choices (see Kihlstrom & Laffont 1979; Caliendo, Fossen & Kritikos 2009, 2010; Caliendo et al. 2014) and there is a large amount

[2]For a review of the recent literature on entrepreneurship-related personality characteristics, see Kerr, Kerr & Xu (2017).

of studies showing that individuals with higher risk tolerance are more likely to be an entrepreneur.[3] Caliendo et al. (2014) report that the overall Big Five traits explain 14 percent of the variance of the probability of being an entrepreneur and risk attitudes alone explain another 8 percent.

A common method to process information based on these observations is to build an entrepreneurship-prone personality profile. Taking the Big Five model as the most prominent example, the profile is characterized as the highest possible score on Extraversion, Conscientiousness and Openness to Experience, and the lowest possible score on Agreeableness and Neuroticism (Schmitt-Rodermund 2004b). A goodness-of-fit measure is then calculated by computing the negative sum of the squared differences between the personality of individual candidates and the statistical reference profile in each of the Big Five traits.[4] Obschonka et al. (2010, p.70) emphasize that participants with a profile close to the reference profile "reported higher levels of early entrepreneurial competence." Obschonka, Schmitt-Rodermund, Silbereisen, Goslin & Potter (2013, p. 105) further argue that such a personality profile is a "particularly robust predictor of entrepreneurial characteristics ... that also reflects a characteristic constellation of traits that makes entrepreneurial behavior more likely." Kösters & Obschonka (2011) conclude that the effectiveness of business advice for entrepreneurs depends on this entrepreneurial Big Five profile.

3 The model

To analyze the performance of such an entrepreneurship-prone personality profile, as discussed in the psychological literature, we, first, introduce a simple model. The model links personality to entrepreneurial abilities and introduces a prediction problem to be solved. Second, we develop an intuitive background regarding the model's environment by relating it to the person- and the variable-oriented approach, usually used to represent an entrepreneurial personality in psychology. Then, we discuss a measure of recommendation performance.

[3]For an overview of studies analyzing the effect of risk attitudes on entrepreneurial activities, see also Kerr et al. (2017).

[4]This kind of fit measure is widely used in psychology, and not only in entrepreneurship; see, *inter alia*, Chapman & Goldberg (2011).

3.1 The problem of predicting entrepreneurial abilities from personality

Consider the following situation: A client of a consultant or mentor plans to start a business, while having incomplete information about her entrepreneurial abilities, and wants to find out whether she has the abilities necessary to become an entrepreneur. To find an answer, she turns to an adviser, who is paid upfront and is only interested in producing a good recommendation result by maximizing the utility of the client. The task of the adviser is to give an informed occupational choice recommendation based on several variables, which, by the nature of a forecast, should be immediately observable. We assume that there are only two occupations: entrepreneur and non-entrepreneur.

Individual variables related to entrepreneurial success consist only of two types. The first type is a factor capturing the information on a personality trait of higher order or of a trait score, $\Gamma \in \mathbb{R}$, that can be immediately observed with reasonable effort.[5] The second type is a measure of entrepreneurial abilities, $\Pi \in \mathbb{R}$, that can, in principle, be observed with some, again reasonable, effort, but only after the specific individual has been sufficiently long exposed to the market as an entrepreneur. Personality trait (or the trait score, which for the rest of the paper is denoted as "personality trait") and abilities are assumed to be stochastic variables. We denote a realization of the personality trait by γ and a realization of abilities by π.

Entrepreneurial abilities have two specific features. First, π measures abilities in relation to some reference point. The most straightforward method to construct π would be to use monetary entrepreneurial income in relation to the monetary income from alternative sources like wage income:

$$\pi = \text{Income from entrepreneurship} - \text{Income from wage work}$$

Other reference points such as non-monetary values, for instance independence resulting from being your own boss[6], are also possible.[7] Second, entrepreneurial

[5]Thus, this simplifying assumption can be relaxed by using a vector of personality variables instead of univariate Γ.

[6]Blanchflower (2000), Hundley (2001), and Benz & Frey (2008a,b) show that entrepreneurs experience higher job satisfaction than wage workers such that non-monetary benefits of entrepreneurship might play a significant role with respect to occupational choices.

[7]There are two possible interpretations of π with respect to risk consistent with the model setting. First, entrepreneurship is not associated with any risk such that π is the deterministic relative income (relative to alternative income). Second, entrepreneurship is associated with risk and π is the average relative income but the client is risk-neutral and only cares about averages.

abilities are inherently *uncertain*. Being perfectly aware of the entrepreneurial abilities of the individual asking for an advice would make the task of giving a good advice trivial to accomplish. However, Π is a typical ex-post variable, not known before the client becomes an entrepreneur, and the client's abilities cannot be directly used as the basis for the advice.

An individual i with $\pi_i = 0$ is neither fit nor unfit for entrepreneurship. Whether an individual is fit for entrepreneurship is determined by a cutoff approach. Let $\tau \in \mathbb{R}_0^+$ denote a cutoff agreed upon by client and adviser such that an individual is suited to become an entrepreneur if $\pi_i > \tau$. An individual is not suited to become an entrepreneur if $\pi_i \leqslant \tau$. τ can be interpreted as the minimal amount of money exceeding non-entrepreneurial income an individual requires to accept that entrepreneurship is more valuable than wage work.

To fully characterize the population of clients, we assume the existence of three more parameters. μ_Γ is the population mean of the personality trait. μ_Π is the population mean of entrepreneurial abilities. ρ is the correlation between personality trait and abilities, measuring the strength and direction of the relationship between both variables. We only consider positive correlations such that $\rho \in (0, 1)$. Without loss of generality, the population variance of the personality trait and entrepreneurial abilities is normalized to 1. Let $\mathbf{v} = [\Gamma, \Pi]^\top$ denote a vector combining personality trait and abilities. We assume that $\mathbf{v}$ is bivariate normal with mean $\mathbf{m} = [\mu_\Gamma, \mu_\Pi]^\top$ and covariance $\mathbf{Q}$, where the covariance between the two variables is ρ, as variances are both 1.

To complete the problem setting, the adviser is assumed to have historical data, Θ, on Γ and Π. Θ is a finite index set where indices represent available historical observations.[8] Furthermore, it is assumed that clients and the historical sample are drawn from the same normal distribution. Note that the latter assumptions might make an advice easier than in reality. In a real-world situation, the characteristics of individuals turning to an adviser can differ from the overall population.

The historical sample consists of $n(\Theta)$ individuals, where $n(\cdot)$ denotes the cardinality of a set, the overall number of its elements. The adviser observes γ_i and π_i for every individual $i \in \Theta$ and can use the common measure of acceptable minimal entrepreneurial abilities, τ, to decompose historical observations into two groups: historical entrepreneurs, $E_\Theta = \{i \in \Theta : \pi_i > \tau\}$ and historical non-entrepreneurs, $E_\Theta^\mathsf{c} = \{i \in \Theta : \pi_i \leqslant \tau\}$.

[8]Typically, even if Π can be measured without any problem, we would only have reliable historical data on it for a subset of individuals because it is a counterfactual for those who were never entrepreneurs.

Theoretically, the same can be done for the client group denoted by Ω (a finite index set of clients) and consisting of $n(\Omega)$ individuals. In practice, since individuals in Θ and Ω are sampled from the same distribution, but as we do not know π_i for all $i \in \Omega$, we can only argue that the same association between personality traits and abilities must hold for Θ and Ω. Yet, we can observe this association only for individuals in the historical sample.

Thus, the problem to be solved is as follows:

Problem. Given the setting above, advice clients $i \in \Omega$ with respect to their relative entrepreneurial abilities, $\pi_i - \tau$, provided that only the client's personality trait γ_i can be observed. Thus, the entrepreneurial abilities of client i must be predicted from her personality, using historical data Θ on personality traits and entrepreneurial abilities.

3.2 The model and psychological research

Our model relates to the two perspectives most dominant in psychological research on how to properly assess the impact of personality on some variable of interest. Magnusson & Törestad (1993) identify the personality- and the variable-oriented approach. In entrepreneurship research, personality- and variable-oriented approaches correspond to the following concepts:

Personality-profile perspective in entrepreneurship research
Conceptually following the ideas of Schumpeter (1934), a researcher using the personality-oriented approach constructs an entrepreneurship-prone reference personality profile (for examples, see Schmitt-Rodermund 2004a; Obschonka et al. 2013). Deviations from the reference profile, measuring goodness of fit of the profile, can be quantified (for a method to measure differences between reference profiles and an observed set of personality traits, see Cronbach & Gleser 1953) and used to predict entrepreneurial behavior. Examples of profile-driven entrepreneurship research are Obschonka et al. (2013), Stuetzer, Goethner & Cantner (2012), and Obschonka & Stuetzer (2017).

Variable-oriented perspective in entrepreneurship research
Variable-oriented approaches "focus on the effects of isolated variables on behavior" (Obschonka et al. 2013, p. 106). They assess the impact of, for instance, a personality trait on some variable of interest—usually, with the help of a linear regression such that trait effects are derived under a *ceteris paribus* condition. A

typical empirical conclusion from the variable-oriented viewpoint is, for instance, as follows:

> Evidence suggests that entrepreneurship is associated with higher levels of extraversion, conscientiousness, and openness and lower levels of agreeableness and neuroticism [. . .] . (Obschonka et al. 2013, p. 106)

Examples of variable-oriented research include Costa, McCrae & Holland (1984), Zhao & Seibert (2006), Zhao et al. (2010), Manso (2016), and Levine & Rubinstein (2017).

With respect to the compatibility of both perspectives and our model, it is possible to establish the following result:

Proposition. *Our recommendation model is consistent with the personality-profile and the variable-oriented approach to model the entrepreneurial personality.*

The proof is provided in Appendix A. The proposition shows that our constructed model mimics the assumptions on the analysis setting in psychology research rather well.

3.3 Measuring performance

Let $\mathbf{a}_i \in \{0, 1\}$ denote an indicator function where $\mathbf{a}_i = 1$ if client $i \in \Omega$ is recommended to become an entrepreneur and $\mathbf{a}_i = 0$ if not. Note that function $\mathbf{a}_i$ depends on the approach applied. Furthermore, let $\mathbf{t}_i = \mathbb{1}\{\pi_i > \tau\} \in \{0, 1\}$, where $\mathbf{t}_i = 1$ if $i \in \Omega$ is actually fit for entrepreneurship and $\mathbf{t}_i = 0$ if not. If clients knew their true entrepreneurial abilities, if information would be perfect, they would self-select into entrepreneurship and non-entrepreneurship according to $\mathbf{t}_i$.

An easy to interpret performance measure can be constructed by comparing recommendations and the actual state of affairs. Thus, let

$$\mathcal{S} = \frac{1}{n(\Omega)} \sum_{i \in \Omega} \mathbb{1}\{\mathbf{a}_i = \mathbf{t}_i\} \tag{1}$$

The indicator in (1) can be interpreted as follows. If $\mathbb{1}\{\mathbf{a}_i = \mathbf{t}_i\} = 1$, recommendation and the actual state of affairs are the same such that the client was recommended entrepreneurship and the client was suitable to become an entrepreneur; or, alternatively, the client was recommended non-entrepreneurship and the client was not an entrepreneur. Put differently,

$$\mathbb{1}\{\mathbf{a}_1 = \mathbf{t}_1\} + \mathbb{1}\{\mathbf{a}_2 = \mathbf{t}_2\} + \cdots + \mathbb{1}\{\mathbf{a}_{n(\Omega)} = \mathbf{t}_{n(\Omega)}\}$$

determines the number of correct recommendations. Consequently, $\mathcal{S} \in [0, 1]$ is the relative number of correct recommendations, the recommendation success rate.

As every individual recommendation success indicator $\mathbb{1}\{\mathbf{a}_i = \mathbf{t}_i\}$ obeys a Bernoulli distribution with success probability p_i and, by construction of recommendation trials, we have $p_1 = p_2 = \cdots = p_{n(\Omega)} = p$, we must have

$$\mathcal{A} = \sum_{i \in \Omega} \mathbb{1}\{\mathbf{a}_i = \mathbf{t}_i\} \sim \text{Binomial}(n(\Omega), p) \tag{2}$$

where p is the probability of a recommendation success given an arbitrary client from set Ω. Note that $\mathbb{E}[\mathcal{A}] = n(\Omega)p$ and $\mathbb{V}[\mathcal{A}] = n(\Omega)p(1-p)$. The success probability p will depend on the distribution of historical and client data, and on the approach used to generate recommendations. Using (2), it is easy to establish that

$$\mathbb{E}[\mathcal{S}] = \frac{1}{n(\Omega)}\mathbb{E}\left[\sum_{i \in \Omega} \mathbb{1}\{\mathbf{a}_i = \mathbf{t}_i\}\right] = \frac{\mathbb{E}[\mathcal{A}]}{n(\Omega)} = p$$

$$\mathbb{V}[\mathcal{S}] = \frac{1}{n(\Omega)^2}\mathbb{V}\left[\sum_{i \in \Omega} \mathbb{1}\{\mathbf{a}_i = \mathbf{t}_i\}\right] = \frac{\mathbb{V}[\mathcal{A}]}{n(\Omega)^2} = \frac{p(1-p)}{n(\Omega)}$$

The variance of recommendation success probability $\mathcal{S}$ is largest at $p = 1/2$ and decreases to both sides such that $\mathbb{V}[\mathcal{S}]$ takes a minimum at $p = 0$ and $p = 1$. Hence, in our problem setting, a high success probability p automatically implies a low recommendation success variance and an increase in the success rate, given that $p \geqslant 1/2$, reduces variance. Therefore, p allows for the derivation of conclusions with respect to the recommendation success probability *and* success variance at the same time.

4 Implementation of profiles

First, we provide a general version of the average-scores approach. Second, we suggest ways on how to optimize recommendations based on average scores. Then, we discuss feasible performance boundaries.

4.1 General average scores

A straightforward algorithm to implement the average-scores approach consists of four steps. The first step is to take historical data, Θ, and divide individuals into two groups by using the cutoff, τ. One group consists of historical entrepreneurs, E_Θ, and the second group consists of historical non-entrepreneurs, E^c_Θ. Second, construct a personality profile for each group. Personality traits are usually measured on Likert scales. This information can be used for taking averages over the personality trait or a trait score γ:

$$\hat{\gamma}_E = \frac{1}{n(E_\Theta)} \sum_{j \in E_\Theta} \gamma_j, \qquad \hat{\gamma}_{E^c} = \frac{1}{n(E^c_\Theta)} \sum_{j \in E^c_\Theta} \gamma_j \tag{3}$$

Third, the adviser should, by employing some statistical test, verify that $\hat{\gamma}_E$ and $\hat{\gamma}_{E^c}$ are significantly different from each other. If there is no significant difference, distinct personality profiles do not exist. Lastly, the adviser recommends entrepreneurship if the client is sufficiently similar to the personality profile of an entrepreneur or

$$\mathbf{a}_i = \begin{cases} 1 & \gamma_i \in h(\epsilon) \\ 0 & \gamma_i \notin h(\epsilon) \end{cases} \quad \text{for } i \in \Omega \tag{4}$$

where $h(\epsilon)$ is a similarity interval given by $h(\epsilon) = (\hat{\gamma}_E - \epsilon, \hat{\gamma}_E + \epsilon)$. The similarity criterion $\epsilon \in \mathbb{R}^+$ is set by the adviser. Internet services specializing in occupational choice recommendations, essentially, employ the general version of the average-scores approach where the similarity criterion is set according to some, rather non-transparent, considerations.

4.2 *Optimized average scores*

As the similarity criterion, ϵ, is a free parameter, it is plausible to assume that the adviser might try to systematically optimize his recommendation performance by setting an appropriate ϵ, based on, for instance, prior recommendation experience. A proper objective to optimize is the expected recommendation success rate, $p = \mathbb{E}[\mathcal{S}]$. Hence, the task of the adviser is to find the following parameter:

$$\epsilon^* = \arg\max_{\epsilon} \left\{ \frac{1}{n(\Omega)} \mathbb{E}\left[\sum_{i \in \Omega} \mathbb{1}\{\mathbf{a}_i(\epsilon) = \mathbf{t}_i\} \right] \right\} \tag{5}$$

where

$$\frac{1}{n(\Omega)} \mathbb{E}\left[\sum_{i \in \Omega} \mathbb{1}\{\mathbf{a}_i = \mathbf{t}_i\} \right] = \mathbb{P}(\mathbf{a} = 1 \wedge \mathbf{t} = 1) + \mathbb{P}(\mathbf{a} = 0 \wedge \mathbf{t} = 0) \tag{6}$$

$$\mathbb{P}(\mathbf{a} = 1 \wedge \mathbf{t} = 1) = \int_{\gamma_E-\epsilon}^{\gamma_E+\epsilon} \int_{\tau}^{\infty} \phi_{\mathbf{m},\mathbf{Q}}(\gamma, \pi) \mathrm{d}\pi \mathrm{d}\gamma \tag{7}$$

$$\mathbb{P}(\mathbf{a} = 0 \wedge \mathbf{t} = 0) = \int_{-\infty}^{\gamma_E-\epsilon} \int_{-\infty}^{\tau} \phi_{\mathbf{m},\mathbf{Q}}(\gamma, \pi) \mathrm{d}\pi \mathrm{d}\gamma + \int_{\gamma_E+\epsilon}^{\infty} \int_{-\infty}^{\tau} \phi_{\mathbf{m},\mathbf{Q}}(\gamma, \pi) \mathrm{d}\pi \mathrm{d}\gamma \tag{8}$$

$\phi_{\mathbf{m},\mathbf{Q}}$ denotes the joint distribution of the personality trait and entrepreneurial abilities. To see that (6) is the probability of a successful recommendation if the adviser uses the average-scores approach, note that there are two ways to generate a correct recommendation. The adviser recommends entrepreneurship and the client is an entrepreneur, which occurs with probability $\mathbb{P}(\mathbf{a} = 1 \wedge \mathbf{t} = 1)$. Alternatively, the adviser does not recommend entrepreneurship and the client is not an entrepreneur occurring with probability $\mathbb{P}(\mathbf{a} = 0 \wedge \mathbf{t} = 0)$. Under the assumption that the joint distribution of the personality trait and entrepreneurial abilities is known and there is some known average personality trait of entrepreneurs γ_E, these probabilities can be computed by (7) and (8).

On the basis of ϵ^*, the adviser can construct an optimized similarity interval $h(\epsilon^*)$ such that, in addition to the general average-scores approach, there exists an optimized version. If the optimized version is used, recommendations are given according to

$$\mathbf{a}_i^* = \begin{cases} 1 & \gamma_i \in h(\epsilon^*) \\ 0 & \gamma_i \notin h(\epsilon^*) \end{cases} \quad \text{for } i \in \Omega \tag{9}$$

Finding ϵ^* requires that the joint distribution of the personality trait and entrepreneurial abilities is perfectly known. In a realistic scenario, this will not hold and parameters must be estimated with historical data. Thus, even if the adviser systematically optimizes, his similarity criterion might deviate from the optimal criterion due to estimation errors.

Example. To provide an example on how to optimize average-scores performance and pitfalls associated with optimization, consider a numerical scenario. Let $\mu_\Gamma = 1$, $\mu_\Pi = -1$, $\rho = 0.8$, and $\tau = 0.1$. For the average personality trait of entrepreneurs, we assume $\gamma_E = \mathbb{E}[\Gamma|\Pi > \tau]$ ($\hat{\gamma}_E$ is just an estimator of $\mathbb{E}[\Gamma|\Pi > \tau]$). The share of entrepreneurs in the population is $1-\Phi(\tau-\mu_\Pi) \approx 14\%$, where Φ is the distribution function of the standard normal. Thus, most clients are not entrepreneurs.

According to (6), the probability of a successful recommendation is the sum of the probability that a client recommended entrepreneurship is an entrepreneur and

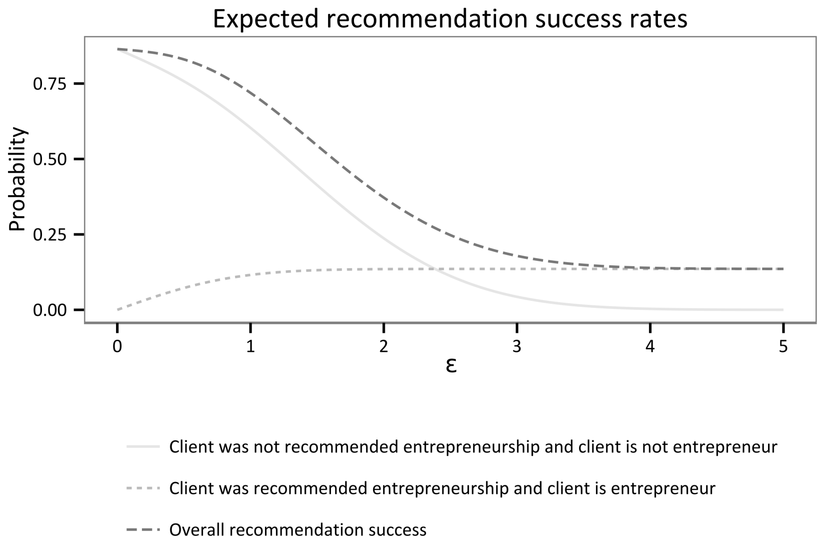


FIGURE 1. An example of changes in expected recommendation success when using the average scores approach with different similarity criteria

that a client not recommended entrepreneurship is not an entrepreneur. In Figure 1, we plot all three probabilities as a function of the similarity criterion, ϵ. The adviser would achieve most recommendation successes if he sets a very strict similarity criterion such that only clients very similar to the entrepreneurship-prone profile are recommended entrepreneurship. This strategy will not necessarily result in an identification of clients suited to become entrepreneurs—in fact, the probability that a client recommended entrepreneurship is an entrepreneur is almost zero—but non-entrepreneurs are identified with a very high probability. The high probability to identify non-entrepreneurs results in a high recommendation success probability. As the similarity criterion increases, the interval $h(\epsilon)$ widens resulting in a higher probability to recommend entrepreneurship. As a consequence, the probability to identify entrepreneurs improves but the probability to identify non-entrepreneurs decreases. What is more important, the probability to identify clients unfit for entrepreneurship decreases more strongly than the probability to identify entrepreneurs such that the overall recommendation success probability decreases.

4.3 Feasible performance bounds

To benchmark average scores, we establish some plausible performance bounds. The first benchmark, which we call the probability-based approach, directly estimates the probability of being suited to become an entrepreneur, and constitutes a feasible upper performance bound. The lower performance bound is given by the toss of an unbiased coin.

The upper bound, the probability-based approach, exploits the well-known result that every conditional distribution of a multivariate normal distribution is normal itself. Conditional on an observation of personality trait, γ_i for $i \in \Omega$, the probability of being suited to become an entrepreneur is given by

$$\mathbb{P}(\Pi > \tau | \Gamma = \gamma_i) = 1 - \int_{-\infty}^{\tau} \phi_{\tilde{\mu}_\Pi, \tilde{\sigma}_\Pi}(\pi) \mathrm{d}\pi \tag{10}$$

where

$$\tilde{\mu}_\Pi = \mu_\Pi + \sigma_\Pi \rho \left(\frac{\gamma_i - \mu_\Gamma}{\sigma_\Gamma} \right), \qquad \tilde{\sigma}_\Pi = (1 - \rho^2) \sigma_\Pi^2$$

The parameters $\mathbf{m}$ and $\mathbf{Q}$ are unknown. Therefore, $\mathbb{P}(\Pi > \tau | \Gamma = \gamma_i)$ is also unknown. However, parameters can be estimated with historical data, to get an estimate of $\mathbb{P}(\Pi > \tau | \Gamma = \gamma_i)$. Let $\mathbf{w}_1, \ldots, \mathbf{w}_{n(\Theta)}$ denote joint observations of personality trait and entrepreneurial abilities. Instead of $\mathbf{m}$, we use

$$\hat{\mathbf{m}} = \frac{1}{n(\Theta)} \sum_{i \in \Theta} \mathbf{w}_i$$

Instead of covariance matrix $\mathbf{Q}$, we use the sample covariance

$$\hat{\mathbf{Q}} = \frac{1}{n(\Theta) - 1} \sum_{i \in \Theta} (\mathbf{w}_i - \hat{\mathbf{m}})(\mathbf{w}_i - \hat{\mathbf{m}})^\top$$

Let φ_i denote the estimated probability that client $i \in \Omega$ is fit for entrepreneurship, an estimate of (10) using estimated parameters $\hat{\mathbf{m}}$ and $\hat{\mathbf{Q}}$. Note that the estimated probability that i is not fit for entrepreneurship is $1 - \varphi_i$. The adviser can recommend entrepreneurship if the probability that i is an entrepreneur exceeds the probability that i is a non-entrepreneur:

$$\mathbf{a}_i^{PBA} = \begin{cases} 1 & \varphi_i > 1 - \varphi_i \\ 0 & \text{else} \end{cases} \quad \text{for } i \in \Omega \tag{11}$$

The probability-based approach can only be applied if the joint distribution of the personality trait and entrepreneurial abilities is (approximately) bivariate normal. If this is not the case, deriving conditional distributions is more difficult.

The lower bound, the coin, generates the following recommendation:

$$\mathbf{a}_i^{COIN} = \begin{cases} 1 & \text{with probability } \frac{1}{2} \\ 0 & \text{with probability } \frac{1}{2} \end{cases} \tag{12}$$

where recommendation probabilities do not depend on data.

5 Performance analysis

In this section, we present the main results of our performace analysis. In preparation, we introduce two desirable properties of a recommendation approach derived from the intuitive idea that an approach should perform substantially better than a coin toss and that recommendation success rates should be sufficiently stable. Second, to perform our analysis under realistic conditions, we estimate our model's parameters with data from the German Socio-economic Panel. Then, we evaluate the recommendation performance of average scores and test whether this approach has the two desirable properties.

5.1 Properties

By introducing the toss of a coin as a benchmark, we set an absolute lower performance boundary. Every approach suitable for occupational choice advice should at least outperform the coin. Thus, the first requirement is that the average recommendation success rate of an approach should be substantially larger than 50%, as 50% is the average success rate of an unbiased coin.[9]

As average scores rely on a similarity criterion, a second sensible requirement is that changing the similarity criterion does not significantly affect recommendation

[9]Note that $p_{\text{COIN}} = \mathbb{E}[S_{COIN}] = \mathbb{P}(\mathbf{a}_{COIN} = 1 \wedge \mathbf{t} = 1) + \mathbb{P}(\mathbf{a}_{COIN} = 0 \wedge \mathbf{t} = 0)$. The coin completely ignores historical and client data such that $\mathbb{P}(\mathbf{a}_{COIN} = a)$ and $\mathbb{P}(\mathbf{t} = t)$ are independent. Hence, we get

$$p_{COIN} = \mathbb{P}(\mathbf{a}_{COIN} = 1)\mathbb{P}(\mathbf{t} = 1) + \mathbb{P}(\mathbf{a}_{COIN} = 0)\mathbb{P}(\mathbf{t} = 0)$$

Given that the probability that an arbitrary individual is an entrepreneur is $\mathbb{P}(\mathbf{t} = 1) = 1-\Phi(\tau-\mu_\Pi)$, we get

$$p_{COIN} = \frac{1}{2}[1 - \Phi(\tau - \mu_\Pi)] + \frac{1}{2}\Phi(\tau - \mu_\Pi) = \frac{1}{2}$$

The variance of recommendation successes rates is easy to derive and given by

$$\mathbb{V}[S_{COIN}] = \frac{p_{COIN}(1 - p_{COIN})}{n(\Omega)} = \frac{1}{4n(\Omega)}$$

success, such that success is reasonably stable. To put it more formally, let ε and ε' denote two different similarity criteria. Let $\mathcal{S}(\varepsilon)$ denote the recommendation success rate of an approach depending on some similarity criterion ε. The measure of performance stability is defined as

$$\Delta(\varepsilon, \varepsilon') = |\mathbb{E}[\mathcal{S}(\varepsilon) - \mathcal{S}(\varepsilon')]|$$

By construction of the measure, we must have

$$0 \leqslant \Delta(\varepsilon, \varepsilon') \leqslant 1$$

Values close to 1 imply unstable performance, while values close to zero imply stability.[10] We require that $\Delta(\varepsilon, \varepsilon')$ is reasonably close to zero.

5.2 Estimation of model parameters

To evaluate average-scores performance with Monte Carlo methods, we use the model in Section 3 as the data generating process (DGP). To make the model as realistic as possible, we estimate model parameters with data. The performance analysis requires the specification of the parameter vector $\boldsymbol{\theta} = [\boldsymbol{\theta}_{DGP}^{\top}, \boldsymbol{\theta}_{Approach}^{\top}]^{\top}$ where

$$\boldsymbol{\theta}_{DGP} = \begin{bmatrix} \mu_\Gamma \\ \mu_\Pi \\ \sigma_\Gamma \\ \sigma_\Pi \\ \rho \end{bmatrix}, \qquad \boldsymbol{\theta}_{Approach} = \begin{bmatrix} \tau \\ \epsilon \end{bmatrix}$$

$\boldsymbol{\theta}_{DGP}$, including variances of trait and abilities, represents our model and fully determines the data generating process. Parameters in $\boldsymbol{\theta}_{Approach}$ are either idiosyncratic to the recommendation approach (similarity criteria) or set by the client (minimal abilities to be an entrepreneur). Consequently, we, first, estimate $\boldsymbol{\theta}_{DGP}$ from data and, then, use the model to analyze performance distributions.

To estimate the model's parameter $\boldsymbol{\theta}_{DGP}$, we use data from the German Socio-economic Panel (GSOEP). The GSOEP is a longitudinal survey of a large representative sample of German individuals and households with coverage from 1984 to 2015 and provides, among other variables, information on personality,

[10]For instance, $\Delta(\varepsilon, \varepsilon') = 1/2$ implies that changing the similarity criterion by a certain amount would change the expected recommendation success rate by 50 percentage points in the same setting indicating that approach performance is unstable.

occupational status, and earnings. We restrict our attention to individuals who provided a self-reported measure of the personal willingness to take risk, and reported monthly income from wage work *and* self-employment.[11]

The relation between the willingness to take risk and entrepreneurial outcomes is, as mentioned in Section 2, well established in the literature. By focusing on individuals who were both wage workers and self-employed during their careers, we avoid the problem of unknown counterfactuals. We take averages over time of entrepreneurial income and wage to reduce noise. The willingness to take risk is measured on a scale from zero (not willing to take risk) to 10 (very high willingness to take risk). In line with Obschonka et al. (2013), we define a statistical reference profile and use the highest reported measure of the willingness to take risk as our trait related to entrepreneurial abilities. In sum, there are 87 available observations, each observation corresponding to a different individual with a certain risk attitude, and experience in entrepreneurship and wage work.[12]

Our model requires that the joint distribution of trait and abilities is bivariate normal. Therefore, data must be transformed, as nominal income differences and risk attitudes are not normally distributed. Sample entrepreneurial abilities is, in line with suggestions in Section 3.1, approximated by average entrepreneurial income (AEI) relative to the average wage (AW). To ensure that the condition of joint normality holds, we take the logarithm such that sample abilities are given by

$$\pi_{Sample} = \log\left(\frac{\text{AEI}}{\text{AW}}\right) = \log(\text{AEI}) - \log(\text{AW})$$

The transformation resulting in π_{Sample} has the downside that the minimal abilities requirement must be applied to the difference in log incomes and not nominal incomes. Consequently, $\pi_i > \tau$, indicating that the individual is fit for entrepreneurship, has no simple interpretation. However, using $\tau = 0$, such that $\log(\text{AEI}) - \log(\text{AW}) > \tau = 0$ and transforming the log difference back to nominal incomes yields the condition

$$\exp(\log(\text{AEI}) - \log(\text{AW})) > \exp(\tau) = \exp(0) = 1$$

which is equivalent to AEI > AW. Hence, we use $\tau = 0$ as the minimal abilities

[11]Self-employment and wage work can take place at the same time or at different time points.

[12]Note that the relatively low number of observations is due to the fact that we need sufficient information about individuals who generated incomes from self-employment *and* wage work. This is also why we had to use the willingness to take risk as information instead of the Big Five. We show below that this choice does not affect the reasoning of our approach.

requirement since this reduces to the simple condition that entrepreneurial income must be larger than the wage.

The original measure of the willingness to take risk γ_* is transformed by applying the Box-Cox transformation:

$$\gamma_{Sample} = \frac{\gamma_*^\lambda - 1}{\lambda}$$

where $\lambda \neq 0$. Given that γ_* is measured on a scale from zero to 10 and we have no observations where $\gamma_* = 0$, and, thus, $\mathrm{d}\gamma_{Sample}/\mathrm{d}\gamma_* = \gamma_*^{\lambda-1} > 0$, an increase in γ_{Sample} can be interpreted as an increase in the willingness to take risk. We set $\lambda = 1.5$, as this value provides a sufficiently good transformation ensuring the bivariate normality of trait and entrepreneurial abilities.

Without loss of generality, we normalize π_{Sample} and γ_{Sample} such that they have a variance of 1, to make variances consistent with the assumptions of our model.

Table 1. Data characteristics

Variable	Min	Max	Mean	Skewness	Kurtosis	p-value for skewness = 0	p-value for kurtosis = 3
Normalized trait	0.28	4.65	2.61	−0.32	2.81	0.19	0.10
Normalized abilities	−3.00	2.12	−0.31	−0.41	3.24	0.93	0.43

Notes: The test of skewness is performed in line with D'Agostino (1970) and the test of kurtosis in line with Anscombe & Glynn (1983).

Table 1 depicts data characteristics including skewness and kurtosis, which are tested against the skewness and kurtosis of a univariate normal distribution, where skewness is zero and kurtosis is 3. The hypothesis that skewness and kurtosis are similar to the normal distribution cannot be rejected at the 5%-level. In addition, we perform the multivariate normality test of Mardia (1974), which cannot reject the hypothesis of multivariate normality at the 5%-level (p-value for multivariate skewness is 0.12 and for multivariate kurtosis 0.09).

Using the assumption of bivariate normality, we estimate the model's parameters by maximum likelihood resulting in

$$\hat{\boldsymbol{\theta}}_{DGP} = \begin{bmatrix} \hat{\mu}_{\Gamma} \\ \hat{\mu}_{\Pi} \\ \hat{\sigma}_{\Gamma} \\ \hat{\sigma}_{\Pi} \\ \hat{\rho} \end{bmatrix} = \begin{bmatrix} 2.61 \\ -0.31 \\ 0.99 \\ 0.99 \\ 0.21 \end{bmatrix}$$

The estimated correlation, $\hat{\rho} = 0.21$, is positive and significantly different from zero at the 5%-level (p-value $= 0.04$). Thus, more willingness to take risk is associated with higher entrepreneurial abilities. Put differently, willingness to take risk predicts entrepreneurial outcomes in line with the entrepreneurial reference type model.

5.3 Performance analysis

The analysis is performed using $\hat{\boldsymbol{\theta}}_{DGP}$ to generate draws from the historical and the client sample. The historical sample is assumed to include 1,000 individuals, whereas the client sample includes 100. Given parameters $\hat{\boldsymbol{\theta}}_{DGP}$, there are two trait profiles. The average trait value for individuals with sufficient entrepreneurial abilities is 2.8, whereas individuals who are not fit for entrepreneurship have an average trait of 2.5.

As τ is fixed ($\tau = 0$), $\boldsymbol{\theta}_{Approach}$ has one parameter that must be set: the similarity criterion ϵ. We assume that $\epsilon \in [0.01, 4.99]$, as performance does not change much for $\epsilon > 4$, and vary the parameter in steps of 0.02, resulting in 250 values. For one parameter value, we simulate performance $M = 10,000$ times and compute expected performance by taking the simulation average

$$\frac{1}{M}\sum_{m=1}^{M} S_m.$$

The lower performance boundary is 0.5 and the upper boundary, based on the probability-based approach (PBA) and simulated with $\hat{\boldsymbol{\theta}}_{DGP}$, is 0.67.

Figure 2 presents simulation results. Expected average-scores performance is depicted as a function of the approach-specific similarity criterion. We also show the two feasible performance bounds. The figure reveals that average-scores performance can be optimized by using a very strict similarity criterion ($\epsilon = 0.01$) such that the maximal recommendation success rate is 62%, which is

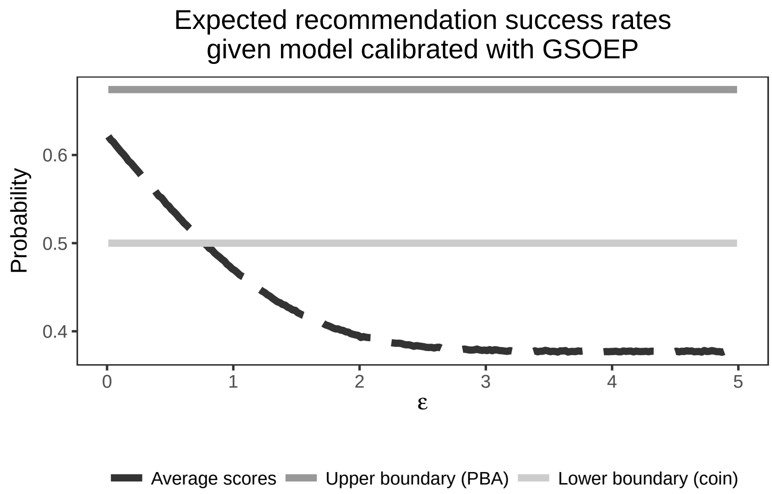


FIGURE 2. Expected recommendation success using model calibrated with GSOEP data

5 percentage points less than the feasible upper performance bound (probability-based approach). However, average-scores performance is very sensitive to the similarity criterion.

We postulated two intuitive requirements an approach should fulfill to be considered as a prediction and recommendation method. The first requirement is that the average recommendation success rate should be substantially larger than the average success rate resulting from the toss of a coin.

TABLE 2. Summary of performance analysis of average scores based on GSOEP

Min	Max	Max − min	Maximal performance as percentage of upper boundary	Minimal performance as percentage of lower boundary
0.38	0.62	0.24	0.92	0.75

Table 2 shows the minimal performance of average scores. The minimal performance is only 38%, which is below the toss of a coin. Thus, average scores violate the first requirement.

The second requirement demands that an approach depending on a similarity criterion is sufficiently robust, in the sense that changing the similarity criterion should not have a large effect on average recommendation success rates. Sufficient recommendation success stability is an important property since data will be plagued by measurement errors and estimations also produce errors. Our robustness measure, $\Delta(\varepsilon, \varepsilon')$, determines how much potential adviser mistakes—setting an inappropriate similarity criterion—cost in terms of average recommendation success rates. In Table 2, we depict the difference between maximal and minimal performance. Using an inappropriate similarity criterion can result in a performance loss of 24 percentage points.

Hence, average scores, respectively profiles, might not exhibit sufficient performance and are not sufficiently stable to be considered as a method for predictions and recommendations.

5.4 *Robustness of results and limitations*

Although the model estimated with data is close to real-world conditions, it only reflects a particular setting, as parameter estimates are based on German data. To check the robustness of our results, we repeated a numerical recommendation experiment using different combinations of parameters resulting in different recommendation settings. We, especially, varied the assumption on the share of entrepreneurs in the population, and the correlation between traits and abilities. The simulation setup and results are described in the Appendix B. Results are fully consistent with those obtained with German data. This even holds for a scenario where personality traits (scores) are highly correlated to abilities.

We also checked whether a simple regression model can outperform the averages approach. Using the same setting as in Section 5.2 and 5.3, we found that predictions generated by the simple model

$$\pi = \mathsf{a} + \mathsf{b}\gamma + \mathsf{e}$$

where a and b are estimated by OLS (e is the error), generated a success rate of 62% on average, which corresponds to the maximal performance of average scores.[13] Thus, even a simple regression is more robust than the average-scores approach, as the performance of the regression approach does not drop below the performance of a coin. Put differently, a model as simple and established as OLS can outperform an average-scores approach on the same data set.

As emphasized in Section 3, we kept the model as simple as possible by using only one trait (which is equivalent to the use of a score over all traits) instead of multiple personality traits. However, we argue that our simple model already captures the most important aspects of our analysis, such that using more traits without adding them up to one score would only increase complexity

[13]The code is provided upon request.

without providing further insights. In this context, we should emphasize a second limitation: In Appendix A, we demonstrate that the personality-oriented and the variable-oriented approach are equivalent. This equivalence holds for the single-factor or score case. It also holds if personality can be sufficiently approximated by a linear combination of normally distributed traits such that

$$\Gamma = \xi_1 \text{trait}_1 + \xi_2 \text{trait}_2 + \xi_3 \text{trait}_3 + \ldots$$

where Γ must be correlated with entrepreneurial abilities. However, if these conditions are violated, the equivalence results might not hold.

A third limitation is that we only analyze simple averages. For a more complex averaging procedure, such as assigning different weights to different traits or assigning multiple weights to differences between traits in the averaging procedure, the results might not hold. However, such approaches are not dominant in the literature, where simple comparisons are more common.

6 Conclusion

The major aim of this contribution is to provide an answer to the question of whether the method of using information on personality scores of successful individuals is helpful to predict the success of an arbitrary individual. While predictions and advice based on a comparison of a prototype with the scores of the individual seeking such advice has been established in the recent literature and in everyday business, it has not been discussed whether this is a proper approach and whether alternative approaches might deliver better results.

Using career advice towards entrepreneurship for illustration purposes, we design a simple framework involving two correlated stochastic variables, generated from a bivariate normal distribution. One variable is interpreted as entrepreneurial abilities. The other variable is an individual personality trait. Our model's setting is consistent with a holistic and a variable-oriented view of the entrepreneurial personality. The problem to solve is to give a recommendation regarding an individual's entrepreneurial abilities by examining only the individual's personality variable, while having historical data on both variables. The data generating process of the problem setting is estimated with German data on personality and entrepreneurial abilities.

We demonstrate that using the average-scores approach sometimes provides even worse predictions and recommendations than the toss of a coin. For instance, if there are many entrepreneurs in the client group of an adviser, using a too strict average-scores similarity criterion will result in too few recommendations for entrepreneurship because many clients with a high probability to be an entrepreneur are recommended against. At the same time, as many entrepreneurs are not properly identified and, due to the strictness of the similarity criterion, recommended non-entrepreneurship, the probability to identify a non-entrepreneur is also low. In such a situation, a coin, always generating 50% correct recommendations, does better. In an estimated model approximating real-world conditions, we find that average scores have a maximal success probability of around 60% and that performance is highly unstable. Other methods such as directly estimating the success probability or a simple regression provide better results.

From a policy perspective, if individuals seek external career advice whether they should become entrepreneurs, they should, rather, avoid following a consultant, entrepreneurship programs, or internet-based questionnaires comparing clients' scores with average scores of entrepreneurs, as they would risk an advice inferior to the toss of a coin. Furthermore, banks and investors should be aware that personality-score evaluations based on average reference personalities, which are relatively cheap and easy to generate, are unlikely to significantly reduce the risk of their loan or investment portfolio. In general, the predictive performance of personality profiles is unlikely to be robust enough to protect against the uncertainty associated with entrepreneurship.

Overall, our results make clear that recommendations based on the method of calculating average profiles may lead only to helpful results if individuals are sufficiently homogenous. Once heterogeneities emerge, and this is what typically happens in all kinds of occupational choices, profiling approaches exhibit a tendency to fail, as they are not able to capture these heterogeneities. This result has consequences for other life outcomes, where these simplistic profiling methods are also applied. Examples are advising the unemployed, predicting career success from a more general point of view beyond entrepreneurship, but also predicting achievements, overall health or delinquency.

Our approach also addresses an earlier discussion tracing back to Gartner (1989) and others who argued that using information on personality traits would be misleading. However, personality traits *per se* do have some predictive power. They do provide important insights on occupational choices or performances in certain occupations or other activities. It is the method that matters. And the commonly used method in psychological research to process information by building simple profiles based on the comparison of the average trait score of individuals who are successful in a certain activity with the average scores of personality traits of others might be misleading, as it contains the high risk of wrong and very costly advice. Future research in particular in psychology needs to analyze what kind of metric methods should be used that take the heterogeneity among individuals better into account. More recent tools—like machine learning—are most probably able to further improve the quality of the advice when compared to average scores.

References

Anscombe, F. & Glynn, W. (1983). Distribution of Kurtosis Statistic for Normal Statistics. *Biometrika*, *70*, 227–234.

Astebro, T. & Chen, J. (2014). The Entrepreneurial Earnings Puzzle. *Journal of Business Venturing*, *29*, 88–105.

Begley, T. & Boyd, D. (1987). Psychological Characteristics Associated with Performance in Entrepreneurial Firms and Smaller Businesses. *Journal of Business Venturing*, *22*, 147–173.

Benz, M. & Frey, B. (2008a). Being Independent is a Great Thing. *Economica*, *75*, 362–383.

Benz, M. & Frey, B. (2008b). The Value of Doing What You Like. *Journal of Economic Behavior and Organization*, *68*, 445–455.

Bernardo, A. & Welch, I. (2001). On the Evolution of Overconfidence and Entrepreneurs. *Journal of Economics & Management Strategy*, *10*, 301–330.

Blanchflower, D. (2000). Self-employment in OECD Countries. *Labour Economics*, *7*, 471–505.

Bono, J., Boles, T., Judge, T., & Lauver, K. (2002). The Role of Personality in Task and Relationship Conflict. *Journal of Personality*, *70*, 311–344.

Borghans, L., Duckworth, A., Heckman, J., & ter Weel, B. (2008). The Economics and Psychology of Personality Traits. *Journal of Human Resources*, *43*, 972–1059.

Bosma, N., Hessels, J., Schutjens, V., Van Praag, M., & Verheul, I. (2012). Entrepreneurship and Role Models. *Journal of Economic Psychology*, *33*, 410–424.

Caliendo, M., Fossen, F., & Kritikos, A. (2009). Risk Attitudes of Nascent Entrepreneurs. *Small Business Economics*, *32*, 153–167.

Caliendo, M., Fossen, F., & Kritikos, A. (2010). The Impact of Risk Attitudes on Entrepreneurial Survival. *Journal of Economic Behavior and Organization*, *76*, 45–63.

Caliendo, M., Fossen, F., & Kritikos, A. (2014). Personality Characteristics and The Decision to Become and Stay Self-Employed. *Small Business Economics*, *42*, 787–814.

Caliendo, M., Kritikos, A., Künn, S., Loersch, C., Schröder, H., & Schütz, H. (2014). Evaluation der Programme Gründercoaching Deutschland. *IZA Research Report*, *61*.

Chapman, B. & Goldberg, L. (2011). Replicability and 40-year Predictive Power of Childhood ARC Types. *Journal of Personality and Social Psychology*, *101*, 593–606.

Costa, P., McCrae, R., & Holland, J. (1984). Personality and Vocational Interests in an Adult Sample. *Journal of Applied Psychology*, *69*, 390–400.

Cronbach, L. & Gleser, G. (1953). Assessing the Similarity Between Profiles. *Psychological Bulletin*, *50*, 456–473.

D'Agostino, R. (1970). Transformation to Normality of the Null Distribution of G1. *Biometrika*, *57*, 679–681.

Fischer, R. & Boer, D. (2014). Motivational Basis of Personality Traits: A Meta-Analysis of Value-Personality Correlations. *Journal of Personality*, *83*, 491–510.

Gartner, W. (1989). Who is an Entrepreneur?' is the Wrong Question. *Entrepreneurship: Theory and Practice*, *12*, 47–68.

Green, D., Müllensiefen, D., Lamb, M., & Rentfrow, P. (2015). Personalty Predicts Musical Sophistication. *Journal of Research in Personality*, *58*, 154–158.

Heckman, J., Stixrud, J., & Urzua, S. (2006). The Effects of Cognitive and Noncognitive Abilities on Labour Market Outcomes and Social Behavior. *Journal of Labor Economics*, *24*, 411–482.

Heller, D., Ferris, D., Brown, D., & Watson, D. (2009). The Influence of Work Personality on Job Satisfaction: Incremental Validity and Mediation Effects. *Journal of Personality*, *77*, 1051–1084.

Helmers, C. & Rogers, M. (2010). Innovation and the Survival of New Firms in the UK. *Review of Industrial Organization*, *36*, 227–248.

Holland, J. (1997). *Making Vocational Choices: A Theory of Vocational Personalities and Work Environments* (3. ed.). Odessa, FL: Psychological Assessment Resources.

Holmes, T. & Schmitz, J. (1990). A Theory of Entrepreneurship and Its Application to the Study of Business Transfers. *Journal of Political Economy*, *98*, 265–294.

Hundley, G. (2001). Why and When are the Self-employed More Satisfied with Their Work? *Industrial Relations*, *40*, 293–316.

Jokela, M. (2009). Personality Predicts Migration within and between U.S. States. *Journal of Research in Personality*, *43*, 79–83.

Kalleberg, A. L. & Leicht, K. T. (1991). Gender and Organizational Performance: Determinanst of Small Business Survival and Success. *Academy of Management Journal*, *34*, 136–161.

Kerr, S., Kerr, W., & Xu, T. (2017). Personality Traits of Entrepreneurs: a Review of Recent Literature. *Harvard Business School Working Paper*, *18–047*.

Kerr, W., Nanda, R., & Rhodes-Kropf, M. (2014). Entrepreneurship as Experimentation. *Journal of Economic Perspectives*, *28*, 25–48.

Kihlstrom, R. & Laffont, J.-J. (1979). A General Equilibrium Entrepreneurial Theory of Firm Formation Based on Risk Aversion. *Journal of Political Economy*, *87*, 719–748.

Koellinger, P., Minniti, M., & Schade, C. (2007). I Think I Can, I Think I Can. *Journal of Economic Psychology*, *28*, 502–527.

Kösters, S. & Obschonka, M. (2011). Public Business Advice in the Founding Process: an Empirical Evaluation of Subjective and Economic Effects. *Environment and Planning C: Government and Policy*, *29*, 123–138.

Levine, R. & Rubinstein, Y. (2017). Smart and Illicit: Who Becomes an Entrepreneur and Do They Earn More? *Quaterly Journal of Economics*, *132*, 963–1018.

Magnusson, D. & Törestad, B. (1993). A Holistic View of Personality: A Model Revisited. *Annual Review of Psychology*, *44*, 427–452.

Manso, G. (2016). Experimentation and the Returns to Entrepreneurship. *Review of Financial Studies*, *29*, 2319–2340.

Mardia, K. (1974). Applications of Some Measures of Multivariate Skewness and Kurtosis for Testing Normality and Robustness Studies. *Sankhy A*, *36*, 115–128.

Mayer, J. & Skimmyhorn, W. (2017). Personality Attributes that Predict Cadet Performance at West Point. *Journal of Research in Personality*, *66*, 14–26.

Obschonka, M., Schmitt-Rodermund, E., Silbereisen, R., Goslin, S., & Potter, J. (2013). The Regional Distribution and Correlates of an Entrepreneurship-prone Personality Profile in the United States, Germany, and the United Kingdom: A Socioecological Perspective. *Journal of Personality and Social Psychology*, *105*, 104–122.

Obschonka, M., Silbereisen, R., & Schmitt-Rodermund, E. (2010). Entrepreneurial Intentions as Development Outcome. *Journal of Vocational Behavior*, *77*, 63–72.

Obschonka, M. & Stuetzer, M. (2017). Integrating Psychological Approaches to Entrepreneurship: The Entrepreneurial Personality System (EPS). *Small Business Economics*, *49*, 203–231.

Quatraro, F. & Vivarelli, M. (2015). Drivers of Entrepreneurship and Post-entry Performance of Newborn Firms in Developing Countries. *The World Bank Research Observer*, *30*, 277–305.

Rauch, A. & Frese, M. (2007). Let's Put the Person back into Entrepreneurship Research. *European Journal of Work and Organizational Psychology*, *16*, 353–385.

Rodionova, Z. (2015). The Personality Test that Could One Day Decide your Credit Score. *The Independent*, *2. September*.

Schmitt-Rodermund, E. (2004a). Pathways to Successful Entrepreneurship: Parenting, Personality, Entrepreneurial Competence, and Interest. *Journal of Vocational Behavior*, *65*, 498–518.

Schmitt-Rodermund, E. (2004b). Pathways to Successful Entrepreneurship: Parenting, Personality, Entrepreneurial Competence, and Interests. *Journal of Vocational Behavior*, *65*, 498–518.

Schumpeter, J. (1934). *The Theory of Economic Development*. Cambridge: Harvard Univ. Press.

Shaver, K. & Scott, L. (1991). Person, Process, Choice: The Psychology of New Venture Creation. *Entrepreneurship Theory & Practice*, *16*, 23–45.

Stewart, W. & Roth, P. (2001). Risk Propensity Differences between Entrepreneurs and Managers. *Journal of Applied Psychology*, *86*, 145–153.

Stuetzer, M., Goethner, M., & Cantner, U. (2012). Do Balanced Skills Help Nascent Entrepreneurs to Make Progress in the Venture Creation Process? *Economics Letters*, *117*, 186–188.

Zhao, H. & Seibert, S. (2006). The Big Five Personality Dimensions and Entrepreneurial Status. *Journal of Applied Psychology*, *91*, 259–271.

Zhao, H., Seibert, S., & Lumpkin, G. (2010). The Relationship of Personality to Entrepreneurial Intentions and Performance: A Meta-Analytic Study. *Journal of Management*, *36*, 381–404.

Appendix A: Proof of consistency

To establish consistency with the profile-based approach, we must essentially answer the following question: What happens to the distribution of the individual trait if we condition on entrepreneurial abilities? Let $\mu_{\Gamma|E}$ denote the mean of Γ for entrepreneurs and let $\mu_{\Gamma|E^c}$ denote the mean of the personality trait for non-entrepreneurs. Similarly, denote the variance of personality trait, Γ, by $\sigma^2_{\Gamma|E}$, respectively $\sigma^2_{\Gamma|E^c}$. It is straightforward to derive that

$$\mu_{\Gamma|E} = \mu_\Gamma + \rho W(\kappa), \qquad \mu_{\Gamma|E^c} = \mu_\Gamma + \rho V(\kappa) \tag{A.1}$$

$$\sigma^2_{\Gamma|E} = 1 - \rho^2 w(\kappa), \qquad \sigma^2_{\Gamma|E^c} = 1 - \rho^2 v(\kappa) \tag{A.2}$$

where $\kappa = \tau - \mu_\Pi$, $W(\kappa) = \phi(\kappa)/[1 - \Phi(\kappa)] > 0$ where $\phi(\cdot)$ is the density and $\Phi(\kappa)$ the distribution function of the standard normal distribution; $V(\kappa) = -\phi(\kappa)/\Phi(\kappa) < 0$; $w(\kappa) = W(\kappa)[1 - W(\kappa)]$; and $v(\kappa) = V(\kappa)[1 - V(\kappa)]$.

As the correlation, ρ, determines how strong the connection is between the personality trait and entrepreneurial abilities, we focus on the role of this parameter. If trait and abilities are independent, the correlation between them is zero such that $\mu_{\Gamma|E} = \mu_{\Gamma|E^c} = \mu_\Gamma$ and $\sigma^2_{\Gamma|E} = \sigma^2_{\Gamma|E^c} = 1$. In such a setting, we cannot construct a distinct personality profile of an entrepreneur. However, if traits and abilities depend on each other with non-zero correlation, there will be a personality profile of an entrepreneur given by $\mu_{\Gamma|E}$. To see this, note that $\rho > 0$ implies

$$|\mu_{\Gamma|E} - \mu_{\Gamma|E^c}| = \rho[W(\kappa) - V(\kappa)] > 0 \tag{A.3}$$

such that there is a difference between the average trait of an entrepreneur and the average trait of a non-entrepreneur. The difference in (A.3) increases in the correlation between trait and entrepreneurial abilities. Furthermore, the variance of the personality trait conditional on being an entrepreneur, $\sigma^2_{\Gamma|E}$, decreases if the correlation between trait and abilities increases, as can be clearly seen in (A.2).

A personality- or profile-oriented approach has the following strategy. It takes the client's personality trait, γ, and compares it to the typical trait, $\mu_{\Gamma|E}$, of an entrepreneur. If Γ and Π are sufficiently correlated, the Γ-values of entrepreneurs will be concentrated in one place and Γ-values of non-entrepreneurs in another. Hence, similarity between the client's γ and profile $\mu_{\Gamma|E}$ is an indication that the client is an entrepreneur. If the correlation is weak, all Γ-values will be located in roughly one place independent from Π such that similarity between the client's trait, γ, and profile $\mu_{\Gamma|E}$ has little meaning.

To show consistency with the variable-oriented approach, let $\Psi \in \mathbb{R}$ denote a normally distributed variable with mean μ_Ψ and variance σ^2_Ψ. Ψ is assumed to capture all factors affecting entrepreneurial abilities that are not related to the personality trait, represented by Γ, such that we can assume that Ψ and personality trait, Γ, are independent. The variable-oriented approach is consistent with the following model of entrepreneurial abilities:

$$\Pi = a\Gamma + b\Psi \tag{A.4}$$

where a and b are nonzero constant scalars. For instance, let Γ represent extraversion (one of the Big Five personality traits). If $a > 0$, more extraversion will increase entrepreneurial abilities, which is in line with previous research (Costa et al. 1984; Zhao & Seibert 2006; Zhao et al. 2010). The difference between the variable-oriented perspective and entrepreneurship-prone profiles is that in the model in (A.4) there is no specific reference profile of an entrepreneur. The assumption underlying (A.4) is that, given $a > 0$, the trait Γ simply positively relates to entrepreneurial abilities, i.e., a higher score in Γ is associated with higher abilities. The model in (A.4) generates a joint distribution of personality trait and abilities that is consistent with our recommendation model. Notice that Π in (A.4) is normal (it is the sum of two normal independent variables) with the following parameters:

$$\mu_\Pi = a\mu_\Gamma + b\mu_\Psi, \qquad \sigma^2_\Pi = a^2 + b^2\sigma^2_\Psi$$

The covariance between Π and personality trait Γ is given by

$$\sigma(\Pi, \Gamma) = a(1 + 2\mu^2_\Gamma) + 2b\mu_\Psi\mu_\Gamma$$

Furthermore, it can be demonstrated that Π and Γ are jointly normal according to the model in (A.4). The joint distribution of Π in model (A.4) and personality trait Γ is bivariate normal if and only if $Y = \alpha\Pi + \beta\Gamma$ is normal for any constant $\alpha, \beta \in \mathbb{R}$. It is obvious that Y is normal if either $\alpha = 0$ or $\beta = 0$, as Π and Γ are both normal. If $\alpha = \beta = 0$, $Y = 0$ with probability 1, which corresponds to a normal distribution with mean and variance zero. Hence, we must demonstrate that Y is normal if α and β are both nonzero. Note that Π and Γ are dependent and correlated. Furthermore, note that

$$Y = \alpha\Pi + \beta\Gamma = \alpha(a\Gamma + b\Psi) + \beta\Gamma = \delta_\Gamma\Gamma + \delta_\Psi\Psi \tag{A.5}$$

where $\delta_\Gamma \equiv \alpha a + \beta$ and $\delta_\Psi \equiv \alpha b$. Using independence and normality of Γ and Π, the moment-generating function of Y is given by

$$M_Y(t) = M_\Gamma(\delta_\Gamma t)M_\Psi(\delta_\Psi t) = \exp\left\{t\delta_\Gamma\mu_\Gamma + \frac{1}{2}\delta_\Gamma^2 t^2\right\} \tag{A.6}$$

$$\times \exp\left\{t\delta_\Psi\mu_\Psi + \frac{1}{2}\delta_\Psi^2\sigma_\Psi^2 t^2\right\}$$

such that

$$M_Y(t) = \exp\left\{t\left[\delta_\Gamma\mu_\Gamma + \delta_\Psi\mu_\Psi\right] + \frac{1}{2}\left[\delta_\Gamma^2 + \delta_\Psi^2\sigma_\Psi^2\right]t^2\right\}$$

(A.6) is the moment-generating function of a normal distribution with mean $\delta_\Gamma\mu_\Gamma + \delta_\Psi\mu_\Psi$ and variance $\delta_\Gamma^2 + \delta_\Psi^2\sigma_\Psi^2$. As Y is normal for any constant α and β, Π and Γ must be bivariate normal. Without loss of generality, we can normalize a such that $a^2 = 1 - b^2\sigma_\Psi^2$ obtaining $\sigma_\Pi^2 = 1$ and $\rho = \sigma(\Pi, \Gamma)$. Hence, as our recommendation model, the model in (A.4) generates a bivariate normal distribution for $[\Gamma, \Pi]^\top$ with mean $\mathbf{m}$ and covariance $\mathbf{Q}$.

Appendix B: Robustness

To check the robustness of the results obtained with GSOEP data, this appendix provides additional simulation results using 1,620 combinations of parameter values.

B.1 Simulation setup

Let $l = 1, \ldots, L$ denote all parameter combinations. Let S^l denote the recommendation performance of an arbitrary approach given parameter combination l. We consider $L = 1,620$ combinations. As before, for every parameter combination, we compute $10,000$ simulations with sample sizes $n(\Theta) = 1,000$ and $n(\Omega) = 100$. Given a sample of historical and client data, we apply three approaches to the same simulated data:

- general average scores (GAS);
- average scores with an optimized similarity criterion, given that **m** and **Q** are known (OAS); and
- the probability-based approach (PBA).

Parameters, which are given in Table B.1, are selected in a way such that a high number of different conditions is covered. Correlation between personality trait and entrepreneurial abilities ranges from weak, $\rho = 0.1$, to strong, $\rho = 0.9$.

TABLE B.1. Variations in parameters

Parameter(s)	Values
μ_Γ, μ_Π	$\in \{-2, -1.5, -1, -0.5, 0, 0.5, 1, 1.5, 2\}$
ρ	$\in \{0.1, 0.3, 0.5, 0.7, 0.9\}$
τ, ϵ	$\in \{0.01, 0.15\}$

ϵ is the non-optimized similarity criterion of average scores. Following the general logic of entrepreneurship-prone personality profiles, we assume that to receive a recommendation for entrepreneurship the client's personality trait must be sufficiently similar to the profile, and that sufficient similarity promises good recommendation results. Hence, we use a rather strict (small) similarity criterion for average scores. However, we consider two different similarity criteria to examine the effect of changes in similarity criteria on average success rates (to test the second requirement). In particular, if $\epsilon = 0.01$, we say that the similarity criterion is strict, whereas $\epsilon = 0.15$ is interpreted as a tolerant similarity criterion.

To compute ϵ^* for the optimized version of average scores, we numerically maximize (6) for every parameter combination. Given the assumption on μ_Π

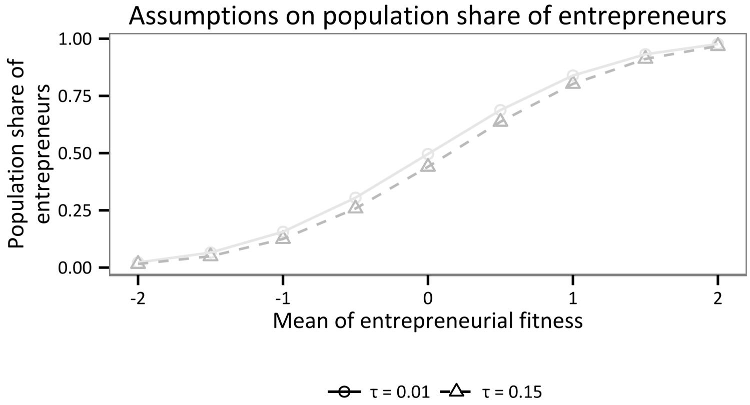


FIGURE B.1. Simulated population shares of entrepreneurs

and τ, we cover a wide range of population shares of entrepreneurs, which is demonstrated in Figure B.1.

B.2 Performance analysis using 1,620 parameter combinations

Benchmarking success probabilities

To get an overview over average performance, we compute the simulation average, approximating $\mathbb{E}[\mathcal{S}^l]$, for every parameter combination l and every approach.

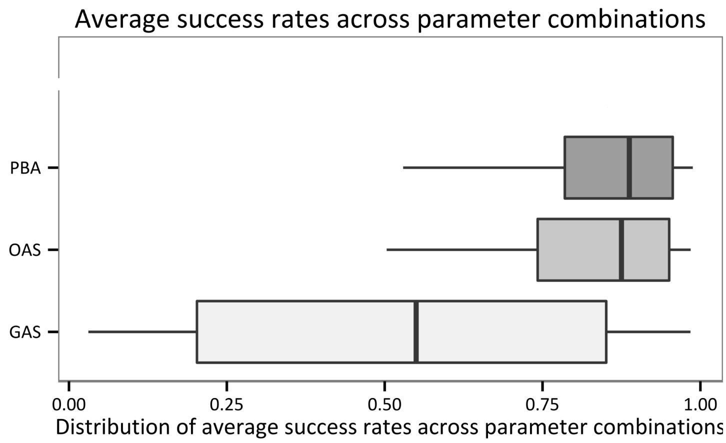


FIGURE B.2. Distribution of average success rates, $p = \mathbb{E}[\mathcal{S}]$

In Figure B.2, we plot the distribution of average recommendation success rates across parameter combinations. Figure B.2 reveals that the general average-scores approach (GAS) substantially underperforms compared to all other approaches.

In Figure B.3, we only show distributions of average success rates for a high correlation between personality trait and entrepreneurial abilities ($\rho = 0.9$). Still,

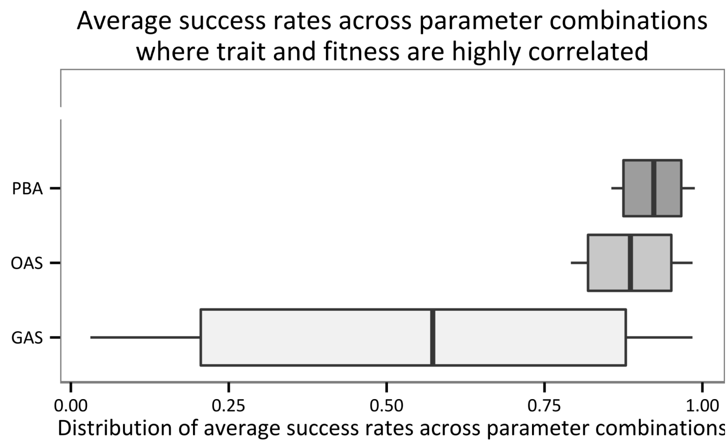
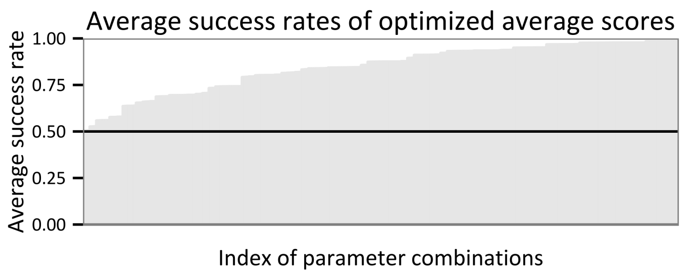


FIGURE B.3. Distribution of average success rates, $p = \mathbb{E}[\mathcal{S}]$, if correlation is high

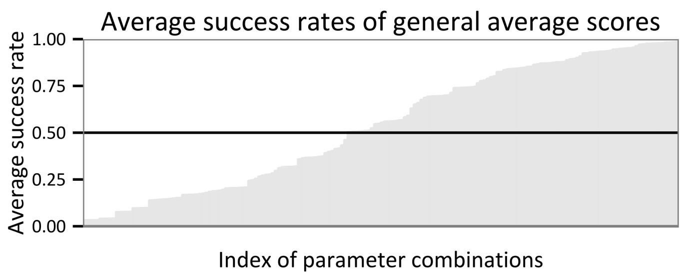
even when correlation between personality trait and entrepreneurial abilities is high, general average scores underperform in comparison to all other approaches.

In contrast to general average scores, optimized average scores (OAS) exhibit high average success rates, which are slightly inferior to the upper boundary of recommendation performance represented by the probability-based approach (PBA). The results on relative performance are consistent with those obtained with the GSOEP calibrated model.

Testing requirements



(a) Average success rates of optimized average scores



(b) Average success rates of general average scores

FIGURE B.4. Recommendation success of average scores

To test the first requirement, in Figure B.4, we plot average recommendation success rates of (a) the optimized average-scores approach and (b) the general average-scores approach as a function of the parameter combinations index, l. Optimized average scores (Figure B.4a) always fulfill the first requirement. In case of general average scores (Figure B.4b), average success rates are smaller than 50%, the approach is inferior to the coin, in about 44% of all parameter combinations. More specific, only if the population share of entrepreneurs is low (about 19% on average, ranging between about 2% and 50%), general average scores outperform the coin with respect to average recommendation success rates.

To test the second requirement, let $l_{\varepsilon,\varepsilon'} = (l_\varepsilon, l_{\varepsilon'})$ denote a pair of parameter combination where all parameters besides the similarity criterion are exactly the same. Our simulation-based measure of robustness, the simulation counterpart of $\Delta(\varepsilon, \varepsilon')$, is

$$\hat{\Delta}(l_{\varepsilon,\varepsilon'}) = \frac{1}{M}\left|\sum_{m=1}^{M} S_m^{l_\varepsilon} - \sum_{m=1}^{M} S_m^{l_{\varepsilon'}}\right|$$

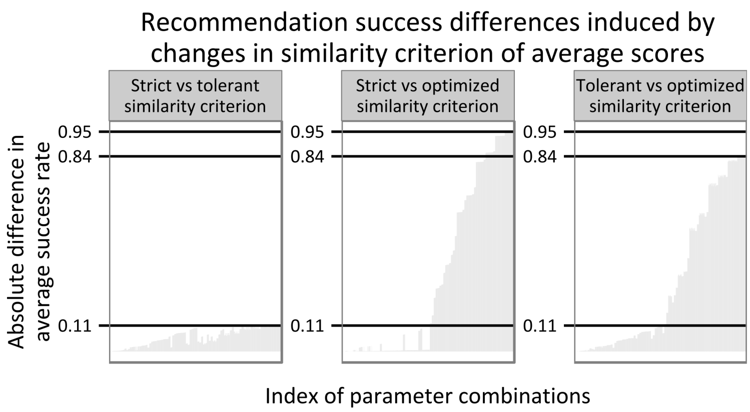


FIGURE B.5. Similarity-criterion-induced changes in average success rates

In Figure B.5, we present robustness measures for average scores. Changing from a strict ($\epsilon = 0.01$) to a tolerant ($\epsilon = 0.15$) similarity criterion, or *vice versa*, changes average recommendation success rates by about 11 percentage points at maximum. The results become more striking when we compare the strict and the tolerant criterion to the optimized similarity criterion ϵ^*. The difference in average success rates between the strict and the optimized criterion is 95 percentage points at maximum, while the success rate difference between the tolerant and the optimized criterion is approx. 84 percentage points at maximum. The results indicate that average scores are not robust—mistakes of the adviser can generate high costs (e.g., a loss in average recommendation success rates of 95 percentage points).