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Abstract: It is often claimed that certain career choices, notably running a business, are associated with excessive confidence in own capabilities. Such a link could partly explain e.g., the surprisingly high number of unsuccessful start-ups. We verify these claims in a sample of marathon runners. We take starting too fast and then slowing down in a marathon race as a proxy for overconfidence. In a sample of over 50 thousand runners, we match marathon pacing data with job titles that are partly reported by the runners themselves and partly identified by us (using runners' names, years of birth, and places of residence to find their personal web sites, social media profiles etc., whenever possible). We observe that job categories have a significant impact on slowing down (as a proxy for overconfidence), also when we control for observable demographic factors (such as age, gender, place of residence). In particular, entrepreneurs tend to be more overconfident than the general population.

Keywords: overconfidence, slowdown, occupational differences, gender differences, selection into professions

JEL codes: D01, L26, J24, J16

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1. Introduction

Overconfidence (OC), considered to be one of the major behavioral biases, has received an increasing amount of attention among psychologists and economists during the past few decades. By far, the most robust demographic effect is the gender difference: males are generally found to be more OC than females. However, other aspects of OC heterogeneity should not be neglected. In particular, possible systematic differences between professions are interesting for at least two reasons. First, because better understanding thereof can facilitate effective management of overconfidence in organizations (see, e.g., Meikle et al., 2016). Second, because it can shed light on the process of self-selection into different professions.

OC has been reported to affect behavior of representatives of different professions. For instance, due to OC, project managers tend to underestimate the probability of risk occurrence and its impact. They also tend to overestimate the likelihood of project's success in terms of cost and time, as well as quality of its deliverables (Fabricius & Büttgen, 2015). Likewise, currency dealers are found to underestimate uncertainty, i.e., to be too certain about the future exchange rate (their 90% confidence intervals cover the actually observed rate much less often than 90% of the time) and overestimate their professional success by rating themselves "better-than-average" (Oberlechner & Osler, 2012). Ben-David et al. (2007) report that overconfident chief financial officers tend to "use lower discount rates to value cash flows, and that they invest more, use more debt, [are] less likely to pay dividends, […] more likely to repurchase shares, and […] use proportionally more long-term, as opposed to short-term, debt". In medicine, OC may cause mistakes in diagnoses (Berner & Graber, 2008).

Santos-Pinto and de la Rosa (2020) explore the origins of OC and analyze how the labor markets are affected by OC among employees. They review the literature in psychology and economics and suggest that OC depends on both personal factors (e.g., ability) and environmental factors (e.g., task difficulty). They find that OC differences among employees could lead to systematic differences in outcomes of labor market (e.g., social welfare, company profits, employee utility). Additionally, the authors suggest that gender differences in confidence could be related to the choice of academic field and could lead to gender wage disparity in competitive markets.

Barron and Gravert (2018) experimentally manipulate the difficulty of a task to induce higher/lower confidence among participants who are then asked to select between two compensation schemes: fixed piece rate and ability-contingent (higher payoff if a participant is in the top half of her group). Under both conditions the exerted efforts are observed. The average effort level is reported to be similar for both compensation schemes. However, the participants (especially those with low ability), once their confidence has been boosted with an easy task, tend to self-select into the ability-contingent scheme more often. Another study addresses the OC among graduates (Hack-Polay, 2020). The author conducts an extensive literature review to argue that university graduates exhibit OC particularly in numerical skills. This may also lead to inefficiencies in the labor market. In particular, OC may limit the graduates' willingness to learn and develop.

There are reasons to expect OC differences between professions. First, theoretical models of OC evolution predict that OC levels depend on human capital accumulation and learning during one's career (Gervais & Odean, 2001; Santos-Pinto, 2020). Particularly, both studies find that OC is expected to decline after an initial increase. Santos-Pinto (2020) additionally shows that for skills with no depreciation (i.e., skills that do not require continuous human capital investments, e.g., clerical skills), OC tends to increase throughout the career. The proposed model predicts that: 1. OC tends to be lower in the fields with higher wage variance[1], 2. OC peak takes place earlier for skills with higher depreciation, 3. OC decreases throughout the career for a small fraction of people, 4. OC tends to be higher given a lower market discount rate. Given different income distributions and the diverse skills required for different professions, it seems plausible that OC levels among professions could be different.

Second, signaling models could explain OC differences between professions. For instance, (Burks et al., 2013) suggests that people tend to be OC because they want to display positive signals about their skills to others. The authors use cognitive skills test results and relative performance judgements of nearly 1000 truck drivers to verify the predictions of three theoretical signaling models: 1. people want to send positive signals about own skills (social signaling), which leads to OC, 2. people tend to be OC because of lack of information about themselves, (Bayesian updating from a common prior, with truthful revelation) and 3. positive self-beliefs cause people to avoid receiving information about their performance, which may induce OC. The latter two models are not supported by the data. Hence, if social signaling (the amount of which is determined by personality traits, i.e., the level of desire for positive signals) might lead to OC, it might be that people in different professions, who have different personalities, would display varying levels of OC. This line of reasoning is further supported

[1] This seems to be counterintuitive, as selection would predict that OC people would naturally tend to be selected into professions where the wage variance is higher. For instance, OC people tend to select into entrepreneurship.

by Schaefer et al. (2004), who find that OC is caused by extroversion. It might be that people in some professions are more/less extrovert, which leads them to different levels of OC.

The third reason for OC differences among professions could be the “sense of power”. Fast et al. (2012) conduct several experiments manipulating the sense of power among participants. The findings suggest that objective sense of power (e.g., getting a position of a supervisor in an experiment) that makes participants feel subjectively powerful leads to OC. Relating this finding to our study, it is possible that certain professions make one feel more powerful, so sense of power could contribute to OC differences between professions. For instance, it would be plausible to expect that managers, who make important decisions, would generally have higher sense of power (as reported by Kocur & Mandal, 2018) than, say, education workers. Overall thus, just like with the concept of depreciation of skills discussed before, it is difficult to actually compare professions in terms of sense of powers, making these predictions difficult to verify without further collection of individual data.

There is also evidence that OC differences may be self-perpetuating (Bressler & Sohmen, 2017; Cheng et al., 2021). Cheng et al. (2021), for instance, find that OC can be socially transmitted inside (but not between) groups and that the transmission perseveres across task types, time (days) and could take place indirectly, i.e., “person to person to person”. This result might be an explanation of OC differences between professions.

There are not that many studies looking at OC differences across professions. Only two groups have been studied more extensively. First, there are studies involving entrepreneurs that typically report that business owners tend to be more OC than the general population (see, e.g., Koellinger et al., 2007; Paul, 2020; Salamouris, 2013). Second, chief executive officers (CEOs) and the consequences of their OC has been widely studied (see, e.g., Billett & Qian, 2008; Brown & Sarma, 2007; Galasso & Simcoe, 2011; Kaplan et al., 2020; Reyes et al., 2020).

Other groups of professions that received some attention in the literature include medical staff (Croskerry & Norman, 2008; Naguib et al., 2019), finance professionals (Kaustia & Perttula, 2012; Torngren & Montgomery, 2004), public decision makers (Liu et al., 2017). For instance, Naguib et al. (2019) conduct an online worldwide survey among anesthesiologists and report that over 90% of them show OC. Kaustia and Perttula (2012) report that their sample of finance professionals are OC, e.g., in terms of better-than-average and probability judgement, and that their debiasing methods might be useful in reducing better-than-average effect, while no result is observed for reducing probability judgement errors. Liu et al. (2017) find in their survey that OC increases with expertise among public decision makers in the US. Skala (2008) reviews OC studies focusing on psychology and finance and reports that the findings on expert judgement tend to be mixed and depend on task difficulty and profession. There are also a few studies that find no differences in OC between different groups. For instance, Arenius et al. (2021) in their laboratory experiment involving entrepreneurs, artists (mainly from visual and performing arts), and other professionals (from banking and education sectors) report no OC differences.

One of very few studies comparing different groups is (Russo & Schoemaker, 1992). They analyze the problem of overprecision among professionals in seven industries: advertising, computers, data processing, money management, petroleum, pharmaceutical and security analysis. Responders are asked to give 90% confidence intervals for 10 figures characterizing their industry. While all exhibit overprecision (provide overly narrow intervals, covering the true value less often than in 9 out of 10 cases), the effect is strongest in pharmaceutical and money management industries and weakest in computers and advertising. Another related paper that compares different groups is (Koehler et al., 2002). The authors address the calibration of experts in five domains: business, law, medicine, meteorology and sports. They report that in all of these domains the experts exhibit miscalibration with significant differences between its magnitudes. The experts from the domains business and meteorology, who tend to have relatively more statistical training, seem to be less biased compared to the remaining domains considered.

The practical problem of bringing time-constrained professionals into the laboratory has been circumvented by Schulz and Thöni (2016) by testing confidence levels of *first year students* of nine fields of study. All students answer five trivia questions and predict their rank within the group of their peers. The difference between predicted and actual rank is used as a measure of overconfidence. Students of Political Science display the strongest tendency for overplacement, followed by Law, Business Administration and Economics. Students of Engineering show no systematic error, while students of Medicine, Natural Science and Humanities tend to underplace themselves. In every field of study men are on average more self-confident than women.

Another study exploring the differences between students from different disciplines is (Yandell, 2017). Using class-level data, this paper measures OC by comparing the expected (revealed in the course evaluation forms) and actual grades of the students. OC is present in all six disciplines included in this study: Business/Management, Decision Science/Information

Technology, Accounting, Finance/Real Estate, Marketing, and Economics. The author reports that Accounting and Economics students seem to be more accurate when predicting their grades.

To the best of our knowledge, there is no study that would provide professionals representing numerous different fields with the same set of questions, thereby making their responses fully comparable. Here, we fill in this gap by investigating marathon runners' pacing strategy. We use slowdown as a proxy for OC and combine data on runners' professions from their own declarations and data available in various internet sources. We thereby come up with a unique data set allowing investigation of OC in professionals in a much more systematic way than was hitherto possible.

2. Method

We focus on marathoners' slowdown and relative slowdown as measures of OC proposed by Krawczyk & Wilamowski (2017, 2019):

$$Slowdown = time\ at\ finish - 2 * (21km\ split),$$

$$Relative\ Slowdown = \frac{time\ at\ finish - 2 * (21km\ split)}{21km\ split}(100\%),$$

where "time at finish" is the time it took the runner to finish the race and "21 km split" is the time it took to complete the first half. Therefore, (relative) slowdown is positive (thus the runner is OC) if the first half is completed faster than the second one.

A reader unconvinced that the (Relative) Slowdown is indeed a valid measure of OC could consider the following. First, physiology literature and sports research suggest that a constant pace is roughly the optimal strategy for marathon runners (see, e.g. Angus, 2014; Joyner, 1991). This is generally the case for moderate weather conditions and flat trails. Indeed, previous studies report that runners who start or finish the race too fast end up with worse finish times (see, e.g. Smyth, 2018). Second, it seems reasonable to assume that majority (if not all) marathon runners are aware of "even pacing strategy" as almost any marathon-related information source (forums, webpages, books, etc.) urges their readers not to start the race too fast. Then, given the availability of speed control and feedback mechanisms like own smart devices and on-site pacesetters, runners generally should be able to follow the constant pace. In reality, however, they usually start too fast and their pace decreases in the second half. A small part of this variation could reasonably be attributed to unexpected events like insignificant injuries that affect the finish times of the runners. Besides, individual characteristics such as physiological factors could explain some variation in slowdown (e.g., that males slow down more than females; Deaner et al., 2014). However, given the previous findings that runners' overly optimistic actual predictions correlate highly with their (Relative) Slowdown (Krawczyk & Wilamowski, 2017, 2019), and that both slowdown measures and actual predictions tend to be affected similarly by individual characteristics, we believe that the Slowdown and the Relative Slowdown are indeed meaningful measures of OC.

3. Data

We focus on 2012-2019 "PZU Warsaw marathon" results, mainly because they contain classification of runners to different professions/groups. When registering for the race, the participants could self-select to one of the professions from the closed list, which is reproduced in Table 1. The list has been pre-determined by the organizers of the race, partly in response to the availability of relevant sponsorship. The organizers would then post the ranking list within each job category on top of the overall results list (the original classification names in Polish are available in Appendix A, Table A1).

Table 1 Number of observations in each category by gender

Group name	Females	Males	Total
Administration	221	927	1,148
Banking	159	1,170	1,329
Bloggers	25	89	114
Education	345	1,045	1,390
Higher education	66	626	692
Insurance	81	627	708
Journalists	59	436	495
Lawyers	138	870	1,008
Medical staff	304	843	1,147
Sales	39	493	532
Students	285	1,411	1,696
Uniformed services	116	2,648	2,764
No category	5,883	32,859	38,742
All runners	7,721	44,044	51,765

Note: Some runners took part in more than one race (and then typically, but not always self-selected to the same category).

All in all, there are 51,765 results with half and finish times indicated, 7,721 (14.9%) of which are for females. The mean (median) age is 38.85 (38). For the year 2014, the available data only include age categories rather than precise age of each runner, thus we use the category mid value for this year (i.e., 45 for age category 40-50, with 75 used for rare age category 70+). Of all the results, 13,023 (25.2%) are for runners with professions classification.

Besides these pre-determined categories, we were able to manually identify job titles of 1135 runners of the 2019 race. We did so by searching their names and home cities on the Internet, finding i.a. their personal web pages and social media profiles. Clearly, there was a risk for finding the wrong person. This made us take a conservative stance and implement a number of measures, see Appendix A (procedures) for details. In particular, we were unable to identify runners coming from big cities and having common names (such as Piotr Kowalski, Warsaw), hence the reduction in sample size. We used International Standard Classification of Occupations (ISCO) to classify those runners into categories. We generally used two-digit categorization (sub-major groups), although in some cases we were forced to merge them into one-digit (major) groups because of overly low number of observations, see Table 2.

Table 2 ISCO codes and the number of runners with identified professions

(sub)group	Description	count
11	Chief executives, senior officials and legislators	114
12	Administrative and commercial managers	131
13	Production and specialized services managers	50
14	Hospitality, retail and other services managers	41
21	Science and engineering professionals	60
22	Health professionals	46
23	Teaching professional	28
24	Business and administration professionals	131
25	Information and communications technology professionals	84
26	Legal, social and cultural professionals	51
31	Science and engineering associate professionals	36
32	Health associate professionals	11
33	Business and administration associate professional	60
34	Legal, social cultural and related associate professionals	50
35	Information and communications technicians	10
4	Numerical and material recording clerks	15
5	Personal service workers	172
6	Market-oriented skilled agricultural workers	3
7	Electrical and electronic trades workers	27

8	Stationary plant and machine operators	15
	Total	1135

On top of this categorization, we were able to identify three major groups jointly accounting for nearly half of these 1135 job titles, see Table 3. All the categorizations were blind, i.e. performed by a research assistant who was unaware of the hypotheses and had no access to marathon data. These procedures were approved by the ethics committee of the Faculty of Economics Sciences of the University of Warsaw.

Table 3 Prominent profession categories, by gender

Group name	**Females**	**Males**	**Total**
Entrepreneur	24	191	215
Manager	35	260	295
IT	3	92	95
All runners 2019	750	3,785	4,535

4. Results

Table 4, 5 and 6 summarize the regression results. Table 4 involves all the runners with pre-determined classifications (N=51,650). In Table 5, interactions with age are additionally reported. Table 6 includes the results with the three prominent professions (available for the 2019 year only). The results including the entire set of ISCO codes is reported in Table A2 in Appendix A.

Table 4 OLS regression results

Variable	**Slowdown**	**Slowdown**	**Relative Slowdown**	**Relative Slowdown**
21km split	0.206***	0.206***	0.001***	0.001***
Male	278.419***	278.358***	3.784***	3.783***
Age	-1.702***	-1.703***	-0.028***	-0.028***
Administration	-11.661	-11.992	-0.19	-0.195
Banking	-2.916	-3.555	-0.037	-0.048
Bloggers	34.387	33.892	0.257	0.25
Education	-40.911*	-40.648*	-0.596*	-0.591*
Higher education	-7.657	-7.62	-0.128	-0.129
Insurance	-3.418	-3.912	0.071	0.062

Journalists	-77.354**	-78.091**	-1.122**	-1.136**
Lawyers	-61.104**	-61.401**	-0.890**	-0.896**
Medical staff	-33.064	-32.976	-0.411	-0.41
Sales	63.949*	63.521*	0.902*	0.895*
Students	109.241***	109.539***	1.503***	1.508***
Uniformed services	25.18	25.363	0.358	0.362
Year dummies	yes	yes	yes	yes
Big city		-16.81		-0.236
Local (Warsaw)		20.75		0.308
Constant	-1332.423***	-1332.252***	-7.563***	-7.564***
N	51650	51650	51650	51650
R2	0.091	0.091	0.057	0.057

legend: * p<.1; ** p<.05; *** p<.01. Note: big cities are the four biggest cities in Poland in terms of population: Warsaw, Cracow, Wroclaw and Lodz.

We observe in Table 4 that males, as well as younger and slower runners (who have a higher 21km split time in seconds) tend to be more OC. Among professional groups, it seems that students and sales professionals (marginal significance) are more OC, while education workers (teachers and school administration), journalists and lawyers tend to be less OC, compared to the general population (no category). The reported category coefficients are jointly significant at 0.1% level (Wald test $p\ value =\ 0.0000$ for all the specifications).

To address the "selection" hypothesis – that people tend to select into professions given their level of OC – we additionally run regressions including interaction with age. To make the comparisons within the specifications more meaningful we use (age-25), assuming that people usually start their professional career when they are around 25 years old.

When we include interactions with age in the models (Table 5), males and slower runners tend to be more OC as before. More importantly, among the professional groups we observe that younger bankers, lawyers, medical staff and uniformed services (i.e., police, soldiers, etc.) seem to generally be OC (positive coefficients, although the coefficients for lawyers and medical stuff are not significant and for banking is marginally significant) and learn to be less OC over time (negative coefficients of (age-25) interaction). The opposite is true for education workers, although the interaction is only significant at 10% level. Students tend to generally be OC. Perhaps for them we observe no age interaction effect as, as it turns out, in our sample the vast majority of students (81%) are below 26. All the category*(age-25) coefficients are jointly significant at 1% level (Walt test p values below 0.0020 for all the specifications). These results are consistent for both dependent variables (slowdown, relative slowdown) and remain significant when we control for the size of home town (a dummy for big cities).

Table 5 OLS regression results: age interactions

Variable	Slowdown	Slowdown	Relative Slowdown	Relative Slowdown
21km split	0.206***	0.206***	0.001***	0.001***
Male	298.089***	298.088***	4.124***	4.124***
(age-25)	0.207	0.21	0.004	0.005
Male*(age-25)	-1.685	-1.689	-0.029*	-0.029*
Administration	-50.599	-51.059	-0.576	-0.583
Banking	75.464*	75.056*	1.137*	1.130*
Bloggers	170.073	169.668	2.404	2.398
Education	-117.842**	-117.633**	-1.590**	-1.585**
Higher education	-67.527	-67.446	-0.627	-0.626
Insurance	23.233	21.84	0.404	0.382
Journalists	-90.518	-91.401	-1.12	-1.134
Lawyers	33.232	33.09	0.491	0.487
Medical staff	42.826	42.96	0.65	0.652
Sales	78.189	77.257	1.013	0.999
Students	116.349***	116.668***	1.616***	1.622***
Uniformed services	101.961***	102.037***	1.430***	1.432***
Administration*(age-25)	2.667	2.675	0.026	0.026
Banking*(age-25)	-6.815**	-6.841**	-0.102**	-0.102**
Bloggers*(age-25)	-15.34	-15.352	-0.242	-0.243
Education*(age-25)	4.748*	4.755*	0.061*	0.061*
Higher education*(age-25)	3.479	3.474	0.029	0.028
Insurance*(age-25)	-1.958	-1.895	-0.024	-0.023
Journalists*(age-25)	1.039	1.044	0.001	0.001
Lawyers*(age-25)	-8.065**	-8.083**	-0.118**	-0.118**
Medical staff*(age-25)	-5.452**	-5.456**	-0.076**	-0.076**
Sales*(age-25)	-1.07	-1.035	-0.009	-0.008
Students*(age-25)	0.246	0.253	0.001	0.001
Uniformed services*(age-25)	-5.607***	-5.597***	-0.078***	-0.078***
Year dummies	yes	yes	yes	yes

Big city		-16.624		-0.231
Local (Warsaw)		21.013		0.312
Constant	-1394.712***	-1394.686***	-8.605***	-8.608***
N	51650	51650	51650	51650
R2	0.092	0.092	0.058	0.058

legend: * p<.1; ** p<.05; *** p<.01

Turning to manually identified professions, we see no significant effect for managers and IT professionals, while a marginally significant result for entrepreneurs is observed (see Table 6). They tend to be more OC than an average runner on the 2019 race. Besides, when adding pre-determined categories into the specification, it seems that sales professionals are also more OC than an average runner of the 2019 race. However, the category coefficients are jointly not significant, with Walt test p values being over 0.1663.

Table 6 OLS regression results including the three prominent professions (2019 race)

Variable	Slowdown	Slowdown	Relative Slowdown	Relative Slowdown
21km split	0.258***	0.259***	0.002***	0.002***
Male	276.565***	281.069***	3.795***	3.862***
Age	-4.603***	-4.349***	-0.069***	-0.067***
Entrepreneur	98.962*	103.234*	1.465*	1.513*
Manager	-11.938	-7.255	-0.163	-0.111
IT	-110.131	-105.49	-1.427	-1.379
Administration		50.598		0.631
Banking		60.021		0.782
Education		45.464		0.75
Higher education		-18.569		-0.336
Insurance		-40.23		-0.567
Journalists		-36.184		-1.021
Lawyers		-135.817		-1.865
Medical staff		54.165		0.684
Sales		201.089**		2.975**
Students		93.912		0.969
Uniformed services		-40.72		-0.618
Constant	-981.623***	-1003.117***	-1.72	-1.973
N	4528	4528	4528	4528

R2	0.09	0.091	0.034	0.036

legend: * p<.1; ** p<.05; *** p<.01

All in all, these results confirm previous findings in the literature that males and entrepreneurs tend to be more OC. Besides, these results shed some light on the selection process and learning, in particular, that bankers and uniformed services tend to be more OC when they are young but become less OC during the course of the career. Also, that education workers tend to be less OC and become more OC as they age.

5. Discussion and conclusions

In this study, we focus on identifying possible differences in overconfidence among different professions. Clearly, our work has some limitations.

First, performance in (one) marathon may be a proxy for overall overconfidence, but is surely a noisy one. On the other hand, the advantage of this measure is that it is unrelated to specific professions in question; for most standard laboratory tasks, one could expect some groups to approach them very differently than others, e.g., bloggers and physicians typically have much less experience with mathematical calculations than accountants or insurance agents.

Second, we had to rely largely on pre-determined categories, some of which were poorly defined or poorly represented; indeed, collecting data on our own was very time consuming and not always successful (and these difficulties would only deepen should we try to apply the search to participants of older races). Relatedly, we wish we could have more variables describing the runners. These were not available though, or collecting them could lead to serious privacy issues.

Subject to these caveats, we believe we came up with interesting and valuable data. From methodological viewpoint, the large effect of being a student and the role of age suggest that one needs to be cautious when extrapolating from typical experiments with undergraduates. Our specifications involving interactions with age also shed important light on selection and learning (Schulz & Thöni, 2016). It appears that we observe age as a significant moderator taming the initial OC in professions in which two conditions are jointly met. First, there are cases, in which one "should" succeed (but sometimes does not); second, in case one does not, there is explicit (negative) feedback.

This is true for doctors (who may lose a seemingly recovering patient), lawyers (who may lose a seemingly sure case), or bankers (who may lose a seemingly secure investment).

The professions in which we do not observe any such learning are those in which there is either only highly diffuse feedback (e.g., education, journalism) or expected success rate is low anyway (sales). Of course, this inference is only preliminary and should best be verified in additional studies, with different sets of categories. Once confirmed, it would suggest that providing regular, unambiguous feedback may be key managing OC in organizations. This is an important insight especially given mixed findings on the effect of feedback on OC (Erat et al., 2020; González-Vallejo & Bonham, 2007; Schumacher et al., 2020).

6. References

Angus, S. D. (2014). Did recent world record marathon runners employ optimal pacing strategies? *Journal of Sports Sciences*. https://doi.org/10.1080/02640414.2013.803592

Arenius, P., Chuah, S.-H., Coate, B., & Hoffmann, R. (2021). The economic psychology of creating and venturing: a comparative behavioural portrait of artists and entrepreneurs. *Small Business Economics*, *57*(2), 721–737. https://doi.org/10.1007/s11187-020-00420-1

Barron, K., & Gravert, C. (2018). Confidence and Career Choices: An Experiment. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3099491

Ben-David, I., Graham, J. R., & Harvey, C. R. (2007). Managerial Overconfidence and Corporate Policies. *NBER Working Paper*.

Berner, E. S., & Graber, M. L. (2008). Overconfidence as a Cause of Diagnostic Error in Medicine. *The American Journal of Medicine*, *121*(5), S2–S23. https://doi.org/10.1016/j.amjmed.2008.01.001

Billett, M. T., & Qian, Y. (2008). Are Overconfident CEOs Born or Made? Evidence of Self-Attribution Bias from Frequent Acquirers. *Management Science*, *54*(6), 1037–1051. https://doi.org/10.1287/mnsc.1070.0830

Bressler, M., & Sohmen, V. S. (2017). The Impact of Entrepreneurial Optimism on Employees. *Global Journal of Entrepreneurship*.

Brown, R., & Sarma, N. (2007). CEO overconfidence, CEO dominance and corporate acquisitions. *Journal of Economics and Business*, *59*(5), 358–379. https://doi.org/10.1016/j.jeconbus.2007.04.002

Burks, S. V., Carpenter, J. P., Goette, L., & Rustichini, A. (2013). Overconfidence and Social Signalling. *The Review of Economic Studies*, *80*(3), 949–983. https://doi.org/10.1093/restud/rds046

Cheng, J. T., Anderson, C., Tenney, E. R., Brion, S., Moore, D. A., & Logg, J. M. (2021). The social transmission of overconfidence. *Journal of Experimental Psychology: General*, *150*(1), 157–186. https://doi.org/10.1037/xge0000787

Croskerry, P., & Norman, G. (2008). Overconfidence in Clinical Decision Making. *The American Journal of Medicine*, *121*(5), S24–S29. https://doi.org/10.1016/j.amjmed.2008.02.001

Deaner, R. O., Carter, R. E., Joyner, M. J., & Hunter, S. K. (2014). Men are more likely than women to slow in the marathon. *Medicine and Science in Sports and Exercise*, *47*(3), 607–616. https://doi.org/10.1249/MSS.0000000000000432

Erat, S., Demirkol, K., & Sallabas, M. E. (2020). Overconfidence and its link with feedback. *Active Learning in Higher Education*. https://doi.org/10.1177/1469787420981731

Fabricius, G., & Büttgen, M. (2015). Project managers' overconfidence: how is risk reflected in anticipated project success? *Business Research*. https://doi.org/10.1007/s40685-015-0022-3

Fast, N. J., Sivanathan, N., Mayer, N. D., & Galinsky, A. D. (2012). Power and overconfident decision-making. *Organizational Behavior and Human Decision Processes*, *117*(2), 249–260. https://doi.org/10.1016/j.obhdp.2011.11.009

Galasso, A., & Simcoe, T. S. (2011). CEO overconfidence and innovation. *Management Science*. https://doi.org/10.1287/mnsc.1110.1374

Gervais, S., & Odean, T. (2001). Learning to Be Overconfident. *Review of Financial Studies*, *14*(1), 1–27. https://doi.org/10.1093/rfs/14.1.1

González-Vallejo, C., & Bonham, A. (2007). Aligning confidence with accuracy: Revisiting the role of feedback. *Acta Psychologica*, *125*(2). https://doi.org/10.1016/j.actpsy.2006.07.010

Hack-Polay, D. (2020). Are graduates as good as they think? A discussion of overconfidence among graduates and its impact on employability. *Education + Training*, *ahead-of-p*(ahead-of-print). https://doi.org/10.1108/ET-10-2018-0213

Joyner, M. J. (1991). Modeling: Optimal marathon performance on the basis of physiological factors. *Journal of Applied Physiology*. https://doi.org/10.1152/jappl.1991.70.2.683

Kaplan, S. N., Sørensen, M., & Zakolyukina, A. A. (2020). What Is CEO Overconfidence? Evidence from Executive Assessments. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3680699

Kaustia, M., & Perttula, M. (2012). Overconfidence and debiasing in the financial industry. *Review of Behavioural Finance*, *4*(1), 46–62. https://doi.org/10.1108/19405971211261100

Kocur, D., & Mandal, E. (2018). The need for power, need for influence, sense of power, and directiveness in female and male superiors and subordinates. *Current Issues in Personality Psychology*, *6*(1). https://doi.org/10.5114/cipp.2018.72200

Koehler, D. J., Brenner, L., & Griffin, D. (2002). The Calibration of Expert Judgment: Heuristics and Biases Beyond the Laboratory. In *Heuristics and Biases* (pp. 686–715). Cambridge University Press. https://doi.org/10.1017/CBO9780511808098.041

Koellinger, P., Minniti, M., & Schade, C. (2007). “I think I can, I think I can”: Overconfidence and entrepreneurial behavior. *Journal of Economic Psychology*. https://doi.org/10.1016/j.joep.2006.11.002

Krawczyk, M., & Wilamowski, M. (2017). Are We All Overconfident in the Long Run? Evidence from One Million Marathon Participants. *Journal of Behavioral Decision Making*, *30*(3), 719–730. https://doi.org/10.1002/bdm.1984

Krawczyk, M., & Wilamowski, M. (2019). Task difficulty and overconfidence. Evidence from distance running. *Journal of Economic Psychology*, *75*(November 2018), 102128. https://doi.org/10.1016/j.joep.2018.12.002

Liu, X., Stoutenborough, J., & Vedlitz, A. (2017). Bureaucratic expertise, overconfidence, and policy choice. *Governance*, *30*(4), 705–725. https://doi.org/10.1111/gove.12257

Meikle, N. L., Tenney, E. R., & Moore, D. A. (2016). Overconfidence at work: Does overconfidence survive the checks and balances of organizational life? In *Research in Organizational Behavior*. https://doi.org/10.1016/j.riob.2016.11.005

Naguib, M., Brull, S. J., Hunter, J. M., Kopman, A. F., Fülesdi, B., Johnson, K. B., & Arkes, H. R. (2019). Anesthesiologists’ Overconfidence in Their Perceived Knowledge of Neuromuscular Monitoring and Its Relevance to All Aspects of Medical Practice. *Anesthesia & Analgesia*, *128*(6), 1118–1126. https://doi.org/10.1213/ANE.0000000000003714

Oberlechner, T., & Osler, C. (2012). Survival of Overconfidence in Currency Markets. *Journal of Financial and Quantitative Analysis*, *47*(1), 91–113. https://doi.org/10.1017/S0022109012000038

Paul, S. R. (2020). Overconfidence: A common psychological attribute of entrepreneurs which leads to firm failure. *New England Journal of Entrepreneurship*.

Reyes, T., Vassolo, R. S., Kausel, E. E., Torres, D. P., & Zhang, S. (2020). Does overconfidence pay off when things go well? CEO overconfidence, firm performance, and the business cycle. *Strategic Organization*. https://doi.org/10.1177/1476127020930659

Russo, J., & Schoemaker, P. (1992). Managing overconfidence. *Sloan Management Review*.

Salamouris, I. S. (2013). How overconfidence influences entrepreneurship. *Journal of Innovation and Entrepreneurship*, *2*(1), 8. https://doi.org/10.1186/2192-5372-2-8

Santos-Pinto, L. (2020). Human Capital Accumulation and the Evolution of Overconfidence. *Games*, *11*(4), 46. https://doi.org/10.3390/g11040046

Santos-Pinto, L., & de la Rosa, L. E. (2020). Overconfidence in Labor Markets. In *Handbook of Labor, Human Resources and Population Economics* (pp. 1–42). Springer International Publishing. https://doi.org/10.1007/978-3-319-57365-6_117-1

Schaefer, P. S., Williams, C. C., Goodie, A. S., & Campbell, W. K. (2004). Overconfidence and the Big Five. *Journal of Research in Personality*, *38*(5), 473–480. https://doi.org/10.1016/j.jrp.2003.09.010

Schulz, J. F., & Thöni, C. (2016). Overconfidence and career choice. *PLoS ONE*. https://doi.org/10.1371/journal.pone.0145126

Schumacher, C., Keck, S., & Tang, W. (2020). Biased interpretation of performance feedback: The role of CEO overconfidence. *Strategic Management Journal*, *41*(6). https://doi.org/10.1002/smj.3138

Skala, D. (2008). Overconfidence in psychology and finance-an interdisciplinary literature review. *Bank i Kredyt*.

Smyth, B. (2018). Fast starters and slow finishers: A large-scale data analysis of pacing at the beginning and end of the marathon for recreational runners. *Journal of Sports Analytics*. https://doi.org/10.3233/jsa-170205

Torngren, G., & Montgomery, H. (2004). Worse Than Chance? Performance and Confidence Among Professionals and Laypeople in the Stock Market. *Journal of Behavioral Finance*, *5*(3), 148–153. https://doi.org/10.1207/s15427579jpfm0503_3

Yandell, D. (2017). Grade Expectations And Overconfidence: Is Economics Different? *Journal for Economic Educators*, *17*(2), 18–28. https://libjournals.mtsu.edu/index.php/jfee/article/view/1520

7. Appendix A

Table A1 The original names of the professional groups

Classification name in Polish	**Equivalent in English**
Klasyfikacja urzędników sektora publicznego	Administration
Klasyfikacja bankowców	Banking
Mistrzostwa Polski blogerów w maratonie	Bloggers
Klasyfikacja dziennikarzy	Journalists
Klasyfikacja handlowców i restauratorów	Sales
Klasyfikacja służb medycznych	Medical staff
Klasyfikacja służb mundurowych	Uniformed services
Klasyfikacja pracowników oświaty	Education
Klasyfikacja prawników	Lawyers

Klasyfikacja studentów	Students
Klasyfikacja ubezpieczeniowców	Insurance
Klasyfikacja akademicka - wykładowcy	Higher education

7.1 Procedures for identifying runners' professions

Browse through the marathon results list.

Stop whenever you find an uncommon Polish full name (e.g., Klaudiusz Piotrowski or Jarosław Miętusiszewski), preferably with a city provided (could be less uncommon when city is small; city missing is acceptable when full name seems truly unique.)

Google it as "name surname". Ignore this runner and resume browsing the marathon results list if there is more than one linkedin hit.

When few hits, browse through them, looking for a website that may tell us the runner's occupation/job title. Typically, Fb/golden line/linkedin/personal of firm's website. We assume it's our guy if 1 OR 2 OR 3 is satisfied AND 4 is satisfied:

1. The same city or a city in vicinity (same voivodship) is mentioned as place of work/residence,
2. A picture as a runner/info (s)he is a runner/info that (s)he is a member of the club also mentioned in the marathon results list is provided,
3. Full name was truly unique to begin with,
4. There is no contradiction in the year of birth.

Ad 4: a contraction would occur in case the googled source listed the person's date of birth as, say, 1960 or a picture showing an obviously old man was provided, whereas he was listed in <30 years of age category in the marathon results lists etc. Remember that someone who was <30 in 2010 may be 40 now etc.

Ignore this runner and resume browsing the marathon results if there is a contradiction in terms of age (4).

If a contradiction in terms of the place of residence (1) is noted, then assume it's still our guy if (2) or (3) is satisfied. Ignore this runner and resume browsing the marathon results if not.

If the runner is identified, copy the address of the website where info found, copy job title, education (level), education (major), firm name, former jobs. A lot of these may be missing.

A lot will be obvious so there is no point searching any further or filling in. I.e., if it's a medical doc or a math teacher, do not waste your time searching for info about education as we can safely assume they went to the med school/university. Also indicate if (s)he seems to belong to one of the following categories:

Administration, Banking, Bloggers, Journalists, Sales, Medical staff, Uniformed services, Education, Lawyers, Students, Insurance, Higher education.

Table A2 OLS regressions including ISCO code groups

Variable	Slowdown	Relative Slowdown	Slowdown	Relative Slowdown	Slowdown	Relative Slowdown
21km split	0.226***	0.002***	0.224***	0.002***	0.225***	0.002***
Male	278.591***	3.902***	284.484**	4.133**	298.859**	4.290**
Age	0.602	0.002				
(Age-25)			-3.077	-0.106	-1.652	-0.09
Group 5	-267.102	-4.303	-240.708	-4.767	-234.609	-4.682
Group 6	437.473	5.258	-4249.816**	-57.310**	-4237.599**	-57.166**
Group 7	-307.11	-4.415	-630.867	-9.845	-612.954	-9.609
Group 8	-90.609	-1.977	457.868	4.333	470.223	4.479
Sub-major group 11	-258.169	-4.158	-185.677	-4.254	-204.409	-4.445
Sub-major group 12	-355.051*	-5.224*	-400.926	-6.453	-416.493	-6.606
Sub-major group 13	-323.698	-4.959	-549.234	-8.434	-560.848	-8.534
Sub-major group 14	-88.507	-1.96	58.032	-0.998	38.881	-1.215
Sub-major group 21	-237.316	-3.703	-574.107	-9.134*	-578.961	-9.171*
Sub-major group 22	-494.132**	-7.045**	-494.466	-7.399	-485.181	-7.273
Sub-major group 23	-130.79	-2.457	113.376	-0.232	98.642	-0.342
Sub-major group 24	-468.628**	-6.989**	-505.073	-8.382*	-527.167	-8.624*
Sub-major group 25	-417.172*	-6.180**	-526.146	-8.305*	-534.764	-8.395*
Sub-major group 26	-267.469	-4.158	-788.914**	-11.333**	-793.935**	-11.369**
Sub-major group 31	-404.632*	-6.530**	-30.293	-3.541	-26.775	-3.493
Sub-major group 32	-443.413	-6.788	-346.576	-7.09	-346.318	-7.09
Sub-major group 33	-211.946	-3.188	-285.703	-5.066	-282.402	-4.991
Sub-major group 34	-257.028	-4.226	-226.624	-4.463	-232.889	-4.525
Sub-major group 35	-521.277*	-7.929*	-697.634	-10.569	-676.604	-10.32
Male*(age-25)			-0.82	-0.021	-1.62	-0.03
Group 5*(age-25)			-0.144	0.067	-1.141	0.055

Group 6*(age-25)			221.825***	2.992***	221.194***	2.985***
Group 7*(age-25)			22.261	0.386	20.924	0.37
Group 8*(age-25)			-38.882	-0.436	-39.852	-0.447
Sub-major group 11*(age-25)			-2.626	0.048	-3.505	0.037
Sub-major group 12*(age-25)			4.015	0.109	3.524	0.103
Sub-major group 13*(age-25)			15.315	0.252	14.884	0.246
Sub-major group 14*(age-25)			-6.595	-0.009	-6.69	-0.01
Sub-major group 21*(age-25)			23.471	0.391	22.389	0.378
Sub-major group 22*(age-25)			1.62	0.066	0.131	0.048
Sub-major group 23*(age-25)			-12.861	-0.09	-12.895	-0.092
Sub-major group 24*(age-25)			3.263	0.12	2.882	0.116
Sub-major group 25*(age-25)			9.576	0.184	8.01	0.166
Sub-major group 26*(age-25)			34.338	0.49	32.505	0.467
Sub-major group 31*(age-25)			-20.213	-0.131	-20.974	-0.14
Sub-major group 32*(age-25)			-6.006	0.044	-6.254	0.041
Sub-major group 33*(age-25)			5.805	0.152	4.856	0.14
Sub-major group 34*(age-25)			-2.234	0.026	-3.202	0.014
Sub-major group 35*(age-25)			12.942	0.206	7.771	0.145
Big city					-1.783	-0.24
Local					85.355	1.226
Constant	-663.915**	2.847	-588.881	4.369	-622.975	3.976
N	1135	1135	1135	1135	1135	1135
R2	0.096	0.048	0.12	0.069	0.122	0.071

legend: * p<.1; ** p<.05; *** p<.01

Note: group six has three observations, so the stars do not mean much; health professionals (22) and business & administration professionals (24) seem to be less OC (surprising, but N=46 and 131, resp., so could just be luck); when we add (age-25) interactions into the specifications (which returns no significant interaction effects) it seems that legal, social and cultural professionals (26) also tend to be less OC, but again N=51; only coefficients from specifications/columns 3 and 5 are jointly significant at 10% level (Walt test p values below 0.0777).

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