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Overconfidence**

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Estimating the Relationship between Skill and Overconfidence

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Abstract

The Dunning–Kruger effect states that the low skilled are overconfident while the high skilled are more accurate in assessing their skill. In apparent support of this effect, many studies have shown that low performers overestimate their performance while high performers are more accurate. This empirical pattern, however, might be a statistical artifact caused by measurement error. We are the first paper to consistently estimate the Dunning–Kruger effect using an instrumental variable approach. In the context of exam grade predictions of economics students, we use students’ grade point average as an instrument for their skill. Our results support the existence of the Dunning–Kruger effect.

JEL: D03; I23

PsycINFO classification: 2220; 3040; 3120

Keywords: Overconfidence, judgment error, measurement error, instrumental variable

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1. Introduction

With the rise of behavioral economics, many psychological concepts have been acknowledged by economists and incorporated into economic models. One of these concepts is overconfidence, which has been used to explain, among other things, financial bubbles (Scheinkman & Xiong, 2003), CEOs' excessive mergers and acquisitions (Malmendier & Tate, 2005), and the excess market entry of entrepreneurs (Camerer & Lovallo, 1999). While most economic studies have not specified the relationship between overconfidence and skill, psychologists Kruger and Dunning (1999) argue that it is generally the low skilled who are most overconfident while the high skilled are, on average, more accurate. This relationship between skill and overconfidence is called the Dunning–Kruger effect (Dunning, 2011). The Dunning–Kruger effect implies that low average overconfidence in a population can hide important heterogeneity and, in particular, those who are least likely to succeed are most likely to overestimate their skill.

The Dunning–Kruger effect has received much attention in the scientific literature: According to Google Scholar, the seminal article by Kruger and Dunning (1999) has been cited more than 2,300 times. Apart from the psychological literature, many researchers in other scientific disciplines seem to have accepted the Dunning–Kruger effect as a psychological fact that can be used to explain individuals' behavior, for example, in law (Tor, 2002), management science (Dane & Pratt, 2007), and medicine (Haun, Zeringue, Leach, & Foley, 2000). In apparent support of the Dunning–Kruger effect, a number of studies have shown that, for many different tasks, low performers usually vastly overestimate their performance while high performers are, on average, more accurate and often even slightly underestimate their performance (Kruger & Dunning, 1999; Burson, Larrick, & Klayman, 2006; Ehrlinger, Johnson, Banner, Dunning, & Kruger, 2008; Ryvkin, Krajč, & Ortmann, 2012).

Performance and overestimation, however, only measure skill and overconfidence with some error. If the Dunning–Kruger effect is estimated by regressing overestimation on performance, measurement error will most likely cause an overestimation of the Dunning–Kruger effect because the same performance measure is used as a measure of skill as well as to calculate overestimation. The intuition behind the bias is as follows: When you consider the measurement error in performance as luck on a test, bad luck on a test will make individuals appear less skilled and at the same time more overconfident. Thus measurement error alone can lead to a negative relationship between skill and overconfidence and the Dunning–Kruger effect could be a statistical artifact.¹ While some studies have tried to overcome estimation bias (Krueger & Mueller, 2002; Ehrlinger et al., 2008), until now no paper has consistently estimated the Dunning–Kruger effect.

In this paper, we estimate the Dunning–Kruger effect in the context of students’ exam grade predictions. To overcome the bias caused by measurement error, we use an instrumental variable (IV) approach in which we use students’ grade point average (GPA) as an instrument for exam performance. Using this approach, we find robust evidence for the Dunning–Kruger effect. As predicted by our methodological discussion, IV estimates are, however, substantially smaller than ordinary least squares (OLS) estimates.

The remainder of the paper is structured as follows: Section 2 discusses the model, key variables, and potential biases when estimating the Dunning–Kruger effect. Section 3 describes the data. Section 4 shows the results and Section 5 concludes the paper.

¹ Krueger and Mueller (2002) were the first to point out that regression effects together with the better-than-average heuristic can explain the observed pattern between performance and overestimation.

2. Estimating the Dunning–Kruger Effect

2.1. Framework

The basic setup of Dunning–Kruger effect studies is that subjects are asked to participate in a test and estimate their performance on this test. Expected performance is elicited either before or after the test and either in absolute terms or relative to their peers. In early studies, researchers showed the mean overestimation by different performance quartiles (Kruger & Dunning, 1999). A general finding was that the bottom quartile performers, on average, vastly overestimated their performance while the top quartile performers were, on average, more accurate. When using relative performance measures, the latter even slightly underestimated their performance (Kruger & Dunning, 1999; Ehrlinger et al., 2008; Ryvkin et al., 2012; Schlösser, Dunning, Johnson, & Kruger, 2013). Krueger and Dunning (1999) explain this pattern in terms of differences in metacognitive skills between low- and high-skilled participants. The intuition behind this explanation is that the skills necessary to perform well are often the same skills that are required to evaluate one’s own performance accurately and those who are unable to assess their own performance well tend to be overconfident. Therefore, low-skilled individuals are overconfident while high-skilled individuals are more accurate about their absolute skill level. However, due to the false consensus effect (Ross, Greene, & House, 1977), which states that people tend to overestimate the degree to which people are similar to them, high-skilled individuals overestimate the skill levels of others and are therefore slightly underconfident in their relative skill.²

To understand the empirical challenges of estimating the Dunning–Kruger effect, we will be more explicit than previous papers on the estimation framework, the definitions of the

² See also Krajc and Ortmann (2008) and Schlösser et al. (2013) for a discussion on an alternative explanation for the Dunning–Kruger effect.

variables used, and potential estimation bias. We model overconfidence oc as a linear function of skill s (omitting individual subscripts throughout to simplify notation):

$$oc = \alpha + \beta_s s + u \quad (1)$$

Overconfidence is the sum of a constant term, α , and a variable component that depends on the individual's skill; u is an idiosyncratic error term that captures individual differences in overconfidence which are unrelated to skill. Looking at estimates of α and β_s jointly provides a simple framework for testing the Dunning–Kruger effect. The Dunning–Kruger effect predicts that overconfidence declines with skill, that is, that β_s is negative. It further predicts that self-assessment errors are asymmetric, that is, overconfidence among low-skilled individuals is large and positive ($\alpha + \beta_s * s$ is large and positive for low values of s) while overconfidence among high-skilled individuals is small in absolute size ($\alpha + \beta_s * s$ is small for high values of s). To isolate the role of measurement error, we assume throughout this section that u is independent of all included variables. This means that if we could observe overconfidence and skill directly, an OLS regression of overconfidence on skill would lead to unbiased estimates of α and β_s . Skill and overconfidence, however, are unobservable and researchers use performance on a test and overestimation of this performance as their respective measures.

2.2. Key Variables

We define skill straightforwardly as the ability in the relevant domain. Performance, however, measures skill with some error, which we can think of as luck. In this context, luck captures all other factors that influence performance. We thus model performance p as the sum of skill s and a classical measurement error component ε :

$$p = s + \varepsilon \quad (2)$$

Classical measurement error means that ε is a random error term, which has a mean of zero and is independent of all variables included in the regression and u . We define overconfidence as the difference between the self-assessed skill level and the actual skill level. Overconfidence can, however, only be measured as overestimation, that is, the difference between expected and actual performance. The key difference between overconfidence and overestimation is that overestimation is partly determined by luck.

We assume that people state their self-assessed skill when asked about their expected performance p_{exp} . Expected performance is therefore the sum of a person's actual skill and overconfidence:

$$p_{exp} = s + oc \quad (3)$$

Besides expected skill, there might be a number of other factors that influence a person's expected performance. When expected performance is elicited before the test, as in this paper, these other factors are arguably unrelated to skill and measurement error and will thus not affect the estimates. When decomposing overestimation into its respective elements, one can see that it is equal to overconfidence minus luck:

$$oe = oc - \varepsilon \quad (4)$$

2.3. Estimating the Relationship between Skill and Overconfidence

One might be tempted to estimate Equation (1) by simply performing an OLS regression of overestimation on performance. To understand the biases associated with this approach, we express Equation (1) in terms of observable variables: It follows from Equations (4) and (2) that $oc = oe + \varepsilon$ and $s = p - \varepsilon$. When we substitute these into Equation (1) and rearrange, we obtain the following expression:

$$oe = \alpha + \beta_s p + u - \varepsilon(1 + \beta_s) \quad (5)$$

Equation (5) shows that p is correlated with the error term because ε is a component of p . Simply regressing overestimation on performance would therefore lead to biased estimates of α and β_s .³ The direction of the overall bias depends on β_s . We expect β_s to be larger than -1 because a β_s smaller than -1 (i.e., more negative) would mean that self-assessed skill would *decline* with actual skill. This is unrealistic because it would imply that those with the lowest skill have the highest self-assessed skill. If β_s is indeed larger than -1, OLS would lead to downward bias, which would mean an overestimation of the Dunning–Kruger effect. The potential magnitude of this bias is substantial: If there were no relationship between skill and overconfidence ($\beta_s = 0$) and performance had a test reliability of 0.5, OLS estimates would, on average, wrongly suggest that a one-point increase in skill would lead to a 0.5 point decrease in overconfidence.⁴

Previously, there have been two attempts to account for this bias. First, Krueger and Mueller (2002) used the split sample method. The split sample method uses two performance measures: one to calculate overestimation and one as a measure of performance measure.⁵ This breaks the mechanical relationship between overestimation and performance. To the extent that performance is measured with classical measurement error, the split sample estimator will be attenuated. Using this approach, Krueger and Mueller do not find evidence of the Dunning–Kruger effect. This is not surprising, because the performance used in their study had a great deal of measurement error, which suggests that the estimates are

³ Testing the Dunning–Kruger effect by showing average overestimation by performance quartiles, as done by Kruger and Dunning (1999), suffers, in principle, from the same biases as estimating it with OLS regression.

⁴ To see why this is the case, remember that the bias of the least squares estimator is $\frac{Cov(p,\omega)}{Var(p)}$, where $\omega = u - \varepsilon(1 + \beta_s)$, which is the composite error term of Equation (5). This bias can also be expressed as $-(1 + \beta_s) \frac{Var(\varepsilon)}{Var(p)} = -(1 + \beta_s) * (1 - r)$, where $r = \frac{Var(s)}{Var(s)+Var(\varepsilon)}$ is the reliability ratio. It follows that, in the absence of an effect of skill on overconfidence ($\beta_s = 0$) and with a test reliability of, say, 0.5, the least squares estimates would mistakenly point to a β_s of -0.5.

⁵ The split sample method is the same as the reduced form of the IV approach we suggest in this paper.

substantially attenuated (the test–retest correlation for their difficult test was 0.17 and for the easy test 0.56).⁶

Second, Ehrlinger et al. (2008) used the reliability-adjusted OLS. The reliability adjustment is carried out by dividing the estimated OLS coefficient by a measure of the test reliability. This, however, is only a valid bias correction method if the coefficient is attenuated. Since the OLS coefficient is likely downward biased, dividing by the test reliability will only increase this bias (for a more extensive discussion on the biases of other estimation methods, see Feld, 2014).

We estimate the Dunning–Kruger effect using an IV approach. To obtain a consistent estimate of β_s we need an IV that is correlated with performance and uncorrelated with u and ε .⁷ We will therefore use a second performance measure as an IV. Note that if the instrument is uncorrelated with ε but correlated with u , the IV estimation corrects for any bias caused by measurement error and thus isolates the empirical relationship between skill and overconfidence, even if this relationship is not causal.

3. Data

Our sample consists of 209 economics students of two second-year bachelor courses, given in March and April 2013 at the School of Business and Economics of Maastricht University in the Netherlands.⁸ A total of 91 percent of the students in our sample were in the same bachelor of economics program and each course was a compulsory course for a different specialization of this program. The remaining 9 percent of students were from other bachelor programs and took this course as an elective. No student took both courses, but 87 percent of

⁶ Note that these studies estimate the Dunning–Kruger effect using relative performance. Using relative performance complicates the analysis, since measurement error is bound at the top and bottom of relative performance and thus the classical measurement error assumption is unrealistic.

⁷ When the error term has zero mean, the IV method will also lead to a consistent estimate of α .

⁸ See Feld, Salamanca, and Hamermesh (2015) for more information on the school’s institutional background.

all students in our estimation sample took the same eight compulsory courses in their first year of study. In total, 165 (79 percent) registered students filled out the questionnaire. The remaining 44 students were not present on the day the questionnaire was distributed in the classroom, either because they missed the particular session or because they had already dropped out of the course. Because Maastricht is close to the German border, the School of Business and Economics has a large share of German students. In our estimation sample, 50 percent of students were German and 30 percent were Dutch; 31 percent were female.

We elicited students' predictions of their exam grade with a questionnaire four weeks before the exam.⁹ Grades were given on a scale from zero (lowest) to 10 (highest) in Course 1 and from one to 10 in Course 2. For both courses, the minimal exam grade necessary to pass the course was 5.5. To ensure that students stated their honest expectations, we incentivized the exam grade predictions by holding a lottery draw in which students could win in each course one of two gift vouchers worth €20 if their prediction was within a range of 0.25 points around their actual exam grade (see the questionnaire in the Appendix). Furthermore, the students were assured that all information would be kept confidential. Information on actual grades was provided by the course coordinators; information on student characteristics and previous grades was taken from the administrative records. The final sample used for estimation comprises 153 students due to missing data on final grades and GPAs.

Table 1 shows the summary statistics for the estimation sample of students' predictions, actual grades, the resulting over- and underestimation, and the students' GPAs at the end of the first year. On average, students significantly overestimated their exam grades by 0.37 ($p = 0.004$).

⁹ We also elicited students' expectations about the percentile of their exam grades and their participation grades. We do not use the participation grade predictions to test the Dunning–Kruger effect because we do not have a suitable instrument for participation grade. We do not use students' percentile expectations because grade percentile is a relative performance measure and the classical measurement error assumption is therefore unrealistic.

Table 1: Predictions, grades, and overestimation

	Mean	S.D.	Min	0.25	0.50	0.75	Max
Predicted exam grade	7.22	0.85	4.50	6.5	7.00	8.00	9.25
Realized exam grade	6.85	1.93	0.00	5.75	7.00	8.00	10.00
Exam overestimation	0.37	1.70	-3.00	-0.75	0.25	1.50	6.20
GPA	7.17	1.15	4.34	6.37	7.17	8.08	9.38

Note: The data in this table are based on the estimation sample. Exam overestimation is equal to the predicted grade minus the realized exam grade.

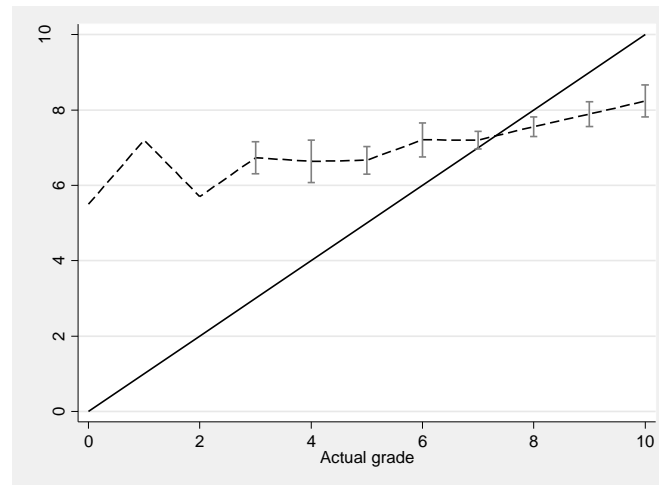
4. Results

Figure 1 plots the average exam predictions against the actual exam grades. If all individuals had perfect foresight about their exam grades, the relation between the predicted and actual grades would be shown by the 45-degree (solid) line. The figure shows the typical pattern of many Dunning–Kruger effect studies: Those with lower grades vastly overestimate their exam grades while those with higher grades slightly underestimate them. However, as discussed in Section 3, the relationship between performance (actual grades) and overestimation shown in Figure 1 is likely to be biased because of measurement error.

We estimate Equation (1) using an IV approach. The dependent variable is the student’s exam overestimation, that is, the difference between the expected and realized exam grades. Since realized exam performance is endogenous, we use the students’ first-year GPA, calculated as the weighted average of all their respective grades at the end of the first year,¹⁰ as an instrument for the following reasons. First, it is correlated with the exam grade, because it is often similar skills that determine grades in different courses. Second, because the last grade of the first-year GPA was graded eight months before the exam students were asked to predict their exam grade, the GPA is arguably uncorrelated with the exam error ε .

¹⁰ The GPA is a weighted average (by ECTS course credit points) of all graded components available at the end of the academic year 2011/2012. The same data are used by Feld and Zölitz (2014). For most of the students, the GPA measure consisted of eight regular courses (6.5 ECTS) and two skills courses (three ECTS) that are compulsory in the first year of the bachelor of economics.

Figure 1: Actual versus predicted exam grades



Note: This figure shows predicted exam grades against actual exam grades. The brackets show the 95 percent confidence interval of the predicted exam grades.

Table 2 shows estimates of the Dunning–Kruger effect. We report OLS estimates in Column (1) as a benchmark. The OLS estimate shows that a one-point increase in the exam grade is associated with a -0.79 decrease in overestimation. This estimate, however, is likely overestimated because of measurement error. Column (2) shows the first stage of the IV estimate. As we would expect, the past GPA is highly predictive of a student’s exam grades. The F -statistics of the excluded instrument are large. Column (2) shows the estimated coefficients of the second stage. The estimated effect of skill is negative and highly significant. This suggests that an increase in skill of one grade point reduces overconfidence by 0.55 grade points, a large effect but substantially smaller (i.e., less negative) than OLS would have suggested. As expected, measurement error causes a substantial bias. These results are remarkably robust: Columns (4) and (5) show that the inclusion of additional controls for student and course characteristics does not change the estimates. We obtain the same qualitative results when we estimate the results for reach course separately and when using any of the grades that make up the GPA individually as an instrument.

Table 2: Estimates of the Dunning–Kruger effect

	(1) OLS Overestimation	(2) First-Stage Exam Grade	(3) Second-Stage Overestimation	(4) First-Stage Exam Grade	(5) Second-Stage Overestimation
Exam grade	-0.7927*** (0.036)		-0.5539*** (0.080)		-0.5733*** (0.065)
GPA		0.9654*** (0.089)		0.9523*** (0.106)	
Constant	5.7991*** (0.265)	-0.0663 (0.696)	4.1632*** (0.601)	0.8820 (0.767)	4.4418*** (0.535)
Controls	No	No	No	Yes	Yes
F-Test excluded instrument		118.9		79.1	
Observations	153	153	153	153	153
R ²	0.806	0.329	0.733	0.402	0.776

Note: Standard errors, in parentheses, are clustered at the tutorial group level. Additional controls include dummy variables for female, German, Dutch, field of study (economics = 1), Course 2, and resit exam. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

These results provide evidence of the Dunning–Kruger effect: The negative coefficient of the (predicted) exam grade shows that overconfidence declines with skill. We can further use the predicted exam grades, our unbiased measure of skill, and the respective estimates of α and β_s in Column (2) of Table 2 to demonstrate that the Dunning–Kruger effect holds in our sample: The predicted overconfidence of the student of the 10th percentile of the skill distribution (predicted exam grade = 5.0) is equal to 1.41 ($4.16 - 0.55 \cdot 5.0$) while the predicted overconfidence of a student of the 90th percentile of the skill distribution (predicted exam grade = 8.42) is equal to -0.47 ($4.16 - 0.55 \cdot 8.42$). In line with the Dunning–Kruger effect, the low-skilled students appear to be very overconfident while the high skilled are more accurate.

5. Conclusion

We present consistent estimates of the Dunning–Kruger effect: Low-skilled students are overconfident while high-skilled students are more accurate in assessing their skill. This relationship, however, is weaker than OLS estimates would suggest. Our findings show that it is crucial to take measurement error into account when estimating the Dunning–Kruger effect.

If this effect is, as Dunning and Kruger argue, a robust psychological phenomenon, it can inform a number of phenomena in which accurate self-assessment is crucial. The existence of the Dunning–Kruger effect means that a low average level of overconfidence can hide important heterogeneity. It is particularly the low skilled, who could often benefit the most from accurate self-assessment, who are the most overconfident.

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Appendix

Questionnaire

The only difference between the questionnaires for course 1 and 2 is that the prediction for the participation grade was only incentivized for course 2. Therefore students could win up to two vouchers in course 1 and up to three vouchers in course 2. Differences between the questionnaires are indicated with “→ *only for course 2*”.

Page 1 of the questionnaire starts on the next page

Dear student,

I am Jan Feld, PhD student in Economics at the School of Business and Economics. My research concerns the relation between grade expectations and realised grades.

I would like to ask you for **your expectations of your grade in the [course name] exam and your participation grade**. Please give your best estimates. You can enter three lotteries if your estimates are close to your actual results. In each lottery you can win one of [two/three] VVV vouchers worth €20. In total, you can win VVV vouchers of [€40/€60].

At the end of the survey, you will be asked to enter your student ID. The ID is required to compare your estimates with your actual results. If you win one of the lotteries, the ID will be used to look up your email so that I can inform you about your win.

I will treat this information confidentially and ensure your anonymity. No individual information will be passed on to anybody (not even your tutor or course coordinator). I will also not report any information which can be used to identify you.

If you have any questions, please feel free to contact me via: j.feld@maastrichtuniversity.nl

Thank you for your cooperation!

Jan Feld

This is how the lotteries are going to work:

Lottery 1: If your exam grade (in your first attempt) is within 0.25 points of your expected grade, you enter a lottery in which two winners are randomly drawn. If you do not attend the first sit, your second sit grade is considered for the lottery. Each winner will receive a VVV voucher worth €20.

Lottery 2: I calculate the actual percentile of your exam grade compared to the exam grades of the first attempts of all students in this course. If your final exam grade is in your expected percentile range, you enter a lottery in which two winners are randomly drawn. Each winner will receive a VVV voucher worth €20.

[Lottery 3: If your actual participation grade is within 0.25 points of your expected participation grade, you enter a lottery in which we randomly draw two winners, who will receive a VVV voucher worth €20.] → *only for course 2*

Questionnaire Grade Expectations - Course [course name]

1. Which grade do you expect to get in the exam of the course [course name]?

If you do NOT intend to attend the first sit, please state your expectations for the second sit (resit).

- I expect to get a ____ . ____ in the exam. [0.00-10.00]

2. Please indicate in which percentile range you expect your exam grade to be in?

The percentile shows the percentage of students in this course which have a lower exam grade (in their first attempt) than you. High values mean high exam grades compared to the exam grades of the other students in this course.

Please mark your expected percentile range with an X.

	1-10%	11%-20%	21%-30%	31%-40%	41%-50%	51%-60%	61%-70%	71%-80%	81%-90%	91%-100%
Your percentile:										
	<i>Worst</i>									<i>Best</i>
	<i>10%</i>									<i>10%</i>

3. Which participation grade do you expect to get in this course?

[Please state your guess rounded to the next quarter point so that it ends with .00, .25, .50 or .75.] → only for course 2

- I expect to get a ____ . ____ as participation grade. [0.00-10.00]

4. Do you consider failing on purpose in the first sit of the exam in this course – either by not attending or by handing in an incomplete exam – in order to get a higher grade in the second sit?

- Yes No

5. What is your gender?

- Male Female

6. What is your student ID?

- ID _____

Please fold this page in half after filling it out.