Master's Thesis Proposal

Institute of Economic Studies
Faculty of Social Sciences
Charles University

Author:	**Bc. Petr Čala**	Supervisor:	doc. Zuzana Havránková
E-mail:	yoursurname@domain.com	E-mail:	zuzana.havrankova@fsv.cuni.cz
Phone:	123456789	Phone:	222 112 309
Specialization:	FFM&B/EEI&EP/ET&M/MEF/CSF	Defense Planned:	February 2023

Notes: The proposal should be 2-3 pages long. Save it as "yoursurname_proposal.doc" and send it to jiri.schwarz@fsv.cuni.cz, tomas.havranek@fsv.cuni.cz, and zuzana.havrankova@fsv.cuni.cz. Subject of the e-mail must be: "JEM001 Proposal (Yoursurname)".

Proposed Topic:

Ability bias in the returns to schooling: How large it is and why it matters

Motivation:

Decades of research in psychology show that general intelligence is one of the most reliable predictors of person's long-term life outcomes (Gottfredson, 1997; Deary, 2001; Deary, 2007; Strenze, 2017; Ozawa et al., 2022). Researchers demonstrated with remarkable consistency that once this g-factor measured by a score on an intelligence test enters a multivariate analysis of life outcomes, the remaining determinants lose their predictive power (hence the phrase "*not much more than g*" in many research titles, incl. Olea & Ree, 1994; Ree & Earls, 1991, 1996; or Ree et al. 1994). Most recently, Ganzach & Patel (2018) reexamine the role of general intelligence in predicting wages, concluding there is *still* not much more than g. Predictive analysis, prevalent in psychology (as noted by Almlund et al., 2011), is indeed a powerful tool for placing an individual efficiently into the labor market. Almlund et al. (2011, p. 34) also note, however, that the predictive analysis (working with correlations) cannot be used for policy analysis (working with causal effects): policy analysis needs counterfactuals to assess how big the impact is once the policy changes.

A major objective of education policies is indeed the improvement of one's capacity to succeed in labor markets. Yet policies could prove inefficient if the estimated effect of education is biased. Herrnstein & Murray (1996) already document that the economic returns (from education or experience) tend to rise among those with high ability. The pioneer meta-study by Bowles et al. (2001), for example, concludes that ignoring a measure of cognitive performance in Mincer (1974) wage equation inflates the returns to schooling. The effect is called ability bias (Griliches, 1977; Heckman & Vytlacil, 2001). Many economists (most prominently Ashenfelter & Rouse, 1999), nevertheless, do not attach to ability bias much importance. Some call out on the omission (Blackburn & Neumark, 1993; Hanushek & Woessmann, 2008), some suggest the non-cognitive abilities are of at least equal importance (Heckman & Rubenstein, 2001), and some even suggest the education does not give the value-added useful for employment (summarized by Caplan, 2018). How much does the ability bias matter? How large are the returns to ability?

I hypothesize that the strongest predictor of life outcomes in psychology literature has an important place in the economic (wage-equation) literature as well. To the best of my knowledge, there is no meta-analysis to private returns to education that would systematically analyze the topic of ability bias.

Hypotheses:

H1: The literature on private returns to education is affected by publication bias.
H2: The publication bias does not plague studies carefully controlling for endogeneity (or causal effects).
H3: Ability bias is statistically and economically important and should be treated for.
H4: The magnitude of returns to education systematically depends on educational level and method of estimation.

Methodology:

I will create a Google Scholar query to identify the literature dealing with Mincer regressions. This wage regression determines earnings as a function of education, ability, the interaction between ability and education, and other determinants. The other determinants most often stand for gender, age, experience, marital status, parental socio-economic status, non-cognitive abilities, hours worked, job tenure, sector- and firm-specific variables, or various environmental variables (such as local unemployment rate). From the wage equation literature, I will collect the coefficient of returns to education (and if the interaction term between ability and education is available, I will use it as well) and its standard error. Much of the wage equation literature is concerned with the private returns to education, thus the reviews of Bowles et al. (2001) and Psacharopoulos & Patrinos (2018) would be a useful place to start with.

In my analysis, I will investigate two aspects of the data: the presence of publication bias and the variance specific to study design. First, I will examine the presence of publication selection bias which occurs when researchers systematically report estimates that are either statistically significant or in line with some strong economic theory (see Stanley et al., 2010). To do so, I will perform the common techniques used in economics, including the graphical test called the funnel plot (Egger et al., 1997) and its more rigorous alternative, the funnel asymmetry test by Stanley (2005). The funnel asymmetry test works with the assumption of a linear relationship between the effect and its standard error as well as with the assumption of exogeneity of the standard error. I will check upon the linearity assumption using several non-linear methods such as the Top 10 method by Stanley et al. (2010), the weighted average of adequately powered by Ioannidis et al. (2017), the selection model by Andrews & Kasy (2019), the stem-based method by Furukawa (2019), and the endogenous-kink model by Bom & Rachinger (2020). I will also include methods that do not require the exogeneity assumption of the standard errors and instead utilize the p-value distribution, such as p-uniform* by van Aert & van Assen (2021) and the latest method due to Elliot et al. (2021).

I will address the heterogeneity behind the effect in question by regressing the effect on a set of explanatory variables capturing study design. Such explanatory variables represent the definition of education, definition of wages, but also wage-equation controls, data specifics such as country variation or granularity, cohort specifics such as gender and age, or workplace character, method characteristics such as OLS, instrumental variables, or natural experiments, and publication specifics such as publication year or the number of citations. Nevertheless, there is a lot of variables to codify, and I do not know ex-ante which of them are important; for example, whether the number of citations covers an aspect (of quality or method) that is not covered systematically by any other variable. Keeping the unimportant variables inside the model could distort the variance of the estimated parameters. Dropping the insignificant variables one by one is a statistically invalid approach. The usual approach to tackle model uncertainty in meta-analysis is via Bayesian model averaging which I will use for my baseline model. In addition to the Bayesian estimation, I will use the Frequentist model averaging as a robustness check (more in Steel, 2020).

Three threats to causal inference often appear in the literature on returns to education: trouble with measurement error (when mechanical error occurs in a variable measuring the education, such as a misreported educational attainment in surveys), reverse causation (better jobs could reinforce or buy education) and omitted variable bias (important correlates are omitted, such as skills, parental education, or health status of a respondent). I want to explore the measurement error in the literature by narration (for example, studies using instrumental variables might attend to the problem), the causality by controlling for quasi-experimental evidence (for example those that use instrumental variable estimations, difference-in-differences, or natural experiments with exogenous force that impacts skills such as reform in education system), and the omitted variable bias by controlling for different aspects that define the wage equation in the literature.

There are, of course, several other issues that could come up as relevant. I might look more closely at the low-wage and high-wage employees separately (Spearman's law could play a role here). There could be problem with cross-country differences in minimum wage setting that distorts the picture. There could be problem with a sheepskin effect (the idea that most of the economic benefit of education, highly correlated with cognition, comes from having a diploma, see Hungerford & Solon, 1987), or with the signaling effect of education itself (the selection inherent in education process signals workers competence, mentioned already in Arrow, 1973, p. 194). I could look on the statistical discrimination theory, suggesting that workers earn average marginal product of workers who somewhat superficially resemble them. These are, nevertheless, avenues that could possibly go beyond the scope of the thesis. I will also try to construct the synthetic estimate of the effect following the estimation practice of the most prominent articles in this literature or following my own critically argued (though inevitably subjective) best-practice choice for the estimation of the effect.

Expected Contribution:

The the best of my knowledge, there is no meta-analysis of this vast literature on private returns to schooling. Following the review of Psacharopoulos & Patrinos (2018) I will construct a data set that entails both returns to education that do control and do not control for ability. I will also gather other possible independent variables that could drive the estimated effect. Using modern meta-analysis techniques, I will explore and correct for publication bias, if present. Next, I plan to apply novel methods, Bayes and Frequentist model averaging, to handle model uncertainty and to investigate the heterogeneity in the literature. Lastly, with the previous outcomes, I would try to construct a synthetic study to estimate the best-practice effect that is corrected for the detected biases.

Outline:

Outline

1. Introduction
   - Motivation, contribution, and main findings
2. Private returns to education
   - Estimating the effect, its importance, trouble with ability
   - Existing surveys of the effect
3. Data collection
   - Selection criteria and final dataset
   - Interpretation of summary statistics
4. Publication bias
   - Why it matters
   - Testing publication bias (funnel plot, linear and non-linear tests, testing subsamples of literature that do and do not account for ability)
5. Heterogeneity
   - Identification of major sources of heterogeneity
   - Testing heterogeneity (using model averaging techniques)
   - Interpretation of the results
6. The best-practice estimate

Conclusion

Core Bibliography:

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Author **Supervisor**