TALLINN UNIVERSITY OF TECHNOLOGY
School of Economics and Business Administration of TUT
Department of Finance and Economics
Chair of Economics

Alexey Volkov

ESTONIAN PISA 2012 RESULTS AS A TOOL FOR MEASURING COGNITIVE SKILLS

Bachelor thesis

Instructor: Senior Researcher Kaire Põder

Tallinn 2015

I hereby declare and confirm with my signature that this Bachelor thesis is exclusively the result of my own autonomous work based on my research and literature published, which is seen in the notes and bibliography used.

Alexey Volkov …………………………

Student code: 104307

Student email address: alexeyvolkov@hot.ee

Instructor: Senior Researcher Kaire Põder

The paper is proofread and eligible

……………………………………………

(signature, date)

Supervisor of Thesis Defence Committee:

Eligible for defence

…………………………………

(position, name, signature, date)

CONTENTS

ABSTRACT

Schooling and human capital investments have been under discussion for showing disappointing results in terms of bursting economic growth. Our ability to explain variations in long-term economic growth among countries can be improved drastically by measuring differences in education achievements more accurately. Luckily, different international test-scores measures of Mathematics, Science, and Reading achievement provide us with such data. In this paper, we focused on Estonian results in Programme of International Student Assessment (PISA) 2012 and tried to understand what kind of inputs are relevant in measuring cognitive skills. We were able to build up a decent education production function and analyse a few regression models. Based on the models we made conclusions about the distribution of education in Estonia and how big is the impact of family background effect. Boys of Estonia do a bit better than girls in Math, while being an immigrant in Estonian results in marginally lower performance. The number of books at home is also statistically significant and can be interpreted as one of the major characteristics in building cognitive skills. However, it remained unclear whether simple possession of more things results in better education, or the parents themselves behind that wealth are important.

Author keywords: human capital, cognitive skills, Programme of International Student Assessment, PISA, education production function.

INTRODUCTION

The discussions on long-term issues have been grabbing attention of developmental policies' researchers over the last 30 years. The main focus has been placed on the effects of schooling related governmental policies on the long-term economic growth rate, specifically. Schooling and human capital investments are believed to have positive effects on economic growth. Unfortunately, implementing growth policy without realising how cognitive skills develop has failed to show significant results in economic outcomes promised by different theoretical growth models. However, there have been some insights that our ability to explain variations in long-term growth among countries can be improved just by measuring differences in cognitive skills more accurately.

Being able to take into account all the relevant impacts on the cognitive skills can help us make major structural changes in various measures of educational policies. Therefore, the aim of this paper is to understand the structure and underlying pattern behind cognitive skills, to point out significant inputs of this process and try to measure them. In order to apply theoretical framework in practice and reach the aims set previously, using some micro datasets is inevitable. As a part of this thesis, we will focus on analysing Estonian results in one of the biggest international assessments of cognitive skills, because it provides us with more than just reliable, but also significantly big database. Using Estonia as an example is connected to the country's successful performance throughout the last two decades, being able to not only perform well, but also has improved its results.

In this paper, the author wishes to get answers to following questions:

- do academic results affect economic growth and to what extent?
- how are cognitive skills generated and how they can be measured?
- what factors influence student performance and how relevant are they?
- what kind of data and how can be used in order to find some evidence of causal relationship?

Moreover, the major objective to be met in this paper is to estimate education production function based on Estonian results in PISA 2012. With a focus on family background effect (FBE), we hypothesised that FBE constitutes a major and statistically significant impact on Estonian PISA 2012 results in Math.

The research was conducted though looking at theoretical points related to the topic and adopting empirical data in order to agree with, or find drawbacks in the statements, previously made.

Various academic papers listed in the reference section were used during documental examination and the empirical data was taken from PISA 2012 results. Main tools for working on the dataset were Stata 13 and Microsoft Excel.

As a result, the thesis is structured as follows. Section 1 presents the gist of academic thought related to the subject and explains how the extensive education production function can be used accompanied by results from international assessment tests. Moreover, this part gives some insights why adding cognitive skills into economic growth models can change the latter for better. Section 2 illustrates the complexity of finding relevant data with more examples of the most common inputs, based on previously found academic evidence. Section 3 begins with explaining what Programme of International Student Assessment (PISA) is and what kind of data it generates. The second part of the very same sections presents descriptive statistics based on Estonian results obtain through that international test in 2012. A short analysis of Estonian performance is done in comparison with top performing countries, neighbouring countries and Organisation for Economic Co-operation and Development (OECD) countries' average. The section is concluded with detailed analysis of some variables, providing some extra information about Estonian system of basic education. Section 4 focuses on building regression models, analysing them and providing some suggestions on further academic research that might be done in this area. Finally, the last part concludes.

I express my deep gratitude to my guide and instructor, Senior Researcher Kaire Põder, who helped me a lot while completing this thesis. I also thank someone who invented "deadlines" for making it possible to finish this paper at all.

1. CONNECTION BETWEEN ECONOMIC GROWTH AND COGNITIVE SKILLS

1.1 Relationship between cognitive skills and economic growth

If we look back in time, then we would see that mostly fiscal and monetary policies were in focus of economists' discussions about government's macroeconomic policies in the 1960s and 1970s. With dominance of Keynesian economic theory, which was born during the Great Depression, it grabbed full attention of many economists with the emphasis on aggregate-demand management in a short term context. The main focus was obtained by studying short-term fluctuations of business cycle. However, even theorists of other schools were troubled with mainly smoothing out the causes of business cycle. These developments were so extreme to an extent that there was no longer-term perspective on macroeconomic policy. (Barro, 2001)

Discussions on longer-term issues started to rapidly arise since the late 1980s and grabbed attention on the effects of governmental policies on the long-term economic growth rate, specifically. This paradigm shift reflects mainly in grown understanding of the difference between prosperity and poverty for a country, depending on the speed of economic growth over the long term. However, it does not mean that fiscal and monetary policies were forgotten. Instead, they got a new kind of context: both are highly influenced and can be interpreted by other policies, and the latter policies are even more important in the long term. One of these policies is developmental policy and it mainly focuses on human capital investments. (*Ibid*)

Schooling and human capital investments have been under discussion for showing disappointing results in terms of bursting economic growth. Growth policy is probably the only policy that has failed to show significant results in economic outcomes promised by different theoretical growth models. A group of economists, Bils and Klenow (2000), found some evidence that greater schooling enrolment in 1960 consistent with an extra year of attainment can be associated with only about 0,30% faster growth in the next thirty years. They also note that in their projections rise in human capital can explain one third (or little more) of economic growth, which remains true even when the effect of schooling on technology adoption is taken into consideration. However, it is clearly not possible to claim schooling be the cause of growth. The relationship can also reflect the reverse causality, thus more schooling (being a normal good) can be a product of growth in income.

However, recent studies by Hanushek and Woessmann (2012) found that our ability to explain variations in long-term growth among countries can be improved drastically just by measuring differences in education achievements more accurately. A vast number of academic literature on cross-country growth regressions has tried to find any evidence of significant positive correlation between average years of schooling as the measure of cognitive skills and economic growth. All analyses assumed that a year of schooling produces the same increase in knowledge and skills, no matter what kind of education system we are dealing with. To bring an example, they assumed that one year of studying in Finland and a year of schooling in Peru create the very same increase in human capital. Moreover, this measure also assumes that education outcomes are primarily affected by formal schooling and non-school factors are said to have insignificant part in those.

There has been no clear evidence on the tight, confirmed causal relationship between cognitive skills and economic growth. However, if cognitive skills from international tests of Math and Science are taken into account and added into the growth model, the entire picture changes. Figure 1 (see next page) portrays annual growth per capita GDP in different world regions between 1960 and 2000, and average scores in international tests (the results were conditioned on GDP per capita in 1960). This figure seems to be able describe annual growth of different world regions for the last decades completely. But still, as many other similar models, neither this one can be used to identify the causal impact of cognitive skills on economic growth. The problem is not in the model itself, but rather in the limited sample of nations (Hanushek, 2012).

On the other hand, an interesting fact is that there was no evidence found of changes in human capital being driven by liberalisation of international trade. It might seem strange, because liberalisation of international trade opens up more possibilities for specialisation and thus focuses on schooling-intensive industries. Even though, open economies are likely to have stronger links between original schooling levels and future shifts of production structure towards schooling-intensive industries, this is only true when studying small samples (like open economies) and less obvious on a large scale with more specifications. Therefore, the link between liberalisation of trade (and economic growth, as a result) and cognitive skills also cannot obviously be called as causal. Nonetheless, some correlation is still present (Ciccone, 2009).

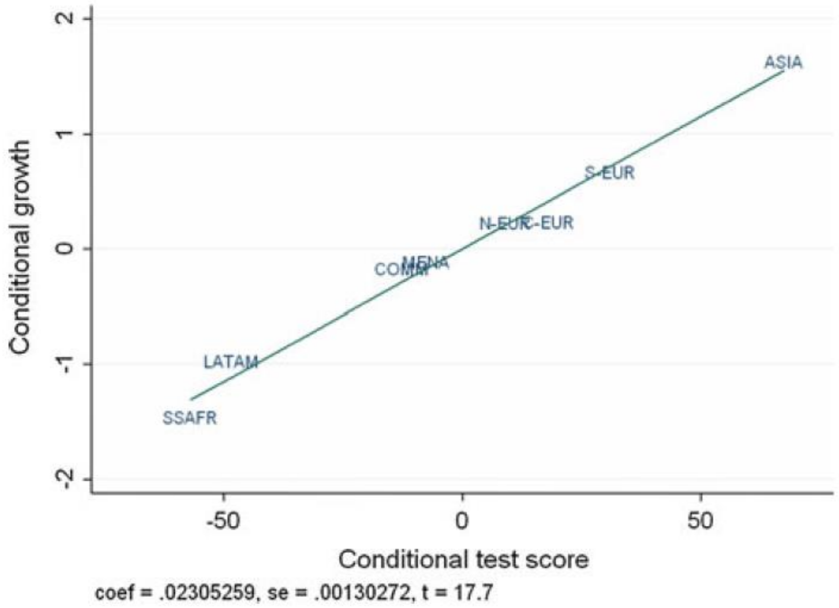

Figure 1. Cognitive Skills and Economic Growth across World Regions. R^2 = 0,985

Sources: (Hanushek, 2012)

Region codes: East Asia and India (ASIA), Central Europe (C-EUR), Commonwealth OECD members (COMM), Latin America (LATAM), Middle East and North Africa (MENA), Northern Europe (N-EUR), Southern Europe (S-EUR), Sub-Saharan Africa (SSAFR)

Even though, the causal relationship between cognitive skills and economic growth cannot be pointed out and explained, we still can talk about obvious impacts of the first on the latter. Cognitive skills undoubtedly have a strong impact on individual earnings; moreover, they have an even stronger and robust influence on economic growth. Models that exclude cognitive skills from their account and use only years of schooling as a measure of economic growth, shall account for about three times variations of the economic outputs (Hanushek, 2008). Therefore, including cognitive skills in a growth model and keeping a track of all factors influencing these skills, can be used in discussions over closing the economic gap between developed and developing countries. Being able to take into account all the relevant impacts on the cognitive skills can help to make major structural changes in schooling institutions possible.

1.2 The extensive education production function

There is a large number of literature on the way to define skills of workers (H), which helps us to understand where these skills might come from. In order to build up a decent policy making process, it is important to see what components there are and which ones of them could and should be affected by policy makers. There has been a disappointing trend in the ways to indicate skills of workers, since they always lacked reliability in terms of quality control. For example, tracking student scores at school alone is not a reliable indicator of one's skills and knowledge (Hanushek, 2002). With coming understanding that there are more than just academic results that shape one's abilities, there have been many attempts to come up with production models that take other factors into account as well.

The most common way to define skills of workers is through the extensive education production function (Hanushek, 2012), according to which the performance of a person i at time t is influenced by a variety of factors including family inputs cumulative to time t (F_{it}), the cumulative quantity and quality of inputs provided by schools (qS_{it}), individual abilities (A_i), and many other related factors (Z_i), such as labour market experience, health, and so on as in:

$$H_{it} = \alpha F_{it} + \beta (qS)_{it} + \gamma A_i + \delta Z_i + \varepsilon \quad (1)$$

The schooling variable consists of two components: school attainment (S) and its quality (q).

Two aspects of this equation are important to mention (Hanushek, 2012):

- A broad variety of influences outside of formal education enter into the production of achievement;
- The production function also emphasises, that some of the components are cumulative, building on a series of inputs over time (like family input).

Human capital is not an obvious variable that can be directly observed. To be useful for any sort of empirical analysis, it is necessary to specify the measurement of the variable *H*. As was discussed above, the vast majority of existing academic work on growth assumes the quantity of schooling of people to be a direct measure of *H* (Hanushek, 2012). Once again, leaving the quality of schooling and assuming that one year of schooling creates the very same amount of knowledge and skills everywhere is wrong and brings us to insignificant results. Therefore, there should be a better alternative for measuring cognitive skills.

Luckily, there is a more compelling alternative to quantity of schooling, and that is measuring *H* directly with international test-scores measures of Mathematics, Science, and Reading achievement. The use of measures of education achievement has few very important advantages that should be pointed out (Hanushek, 2012):

- All the variations in the knowledge and ability that schools produce can be captured and then used as a measurement of subsequent economic success;
- Skills from any source - families, schools, and ability – are incorporated in this case;
- Provided data allows for differences in performance among students with varying quality of education (even if the years of schooling are the same). This opens up some space for further investigation of different policy implications.

2. DEFINING INPUTS AFFECTING COGNITIVE SKILLS

2.1 Finding relevant factors

The irrelevance of comparing students merely on their performance at school stresses obvious necessity to include various factors outside schools into any analyses of cognitive skills. Of course, leaving out all "non-measurable", difficult-to-track variables seems natural from a policy point of view (Hanushek, 2002). Nonetheless, it may no longer be the case, because ignoring these factors will definitely lead to different and biased results. Recently, there have been some issues that require closer administrative attention and thus provide with some specifics about omitted factors. First of all, rising intense in discussions about kindergarten education activities, preschool and after school programmes, parent education and the like, highlights relevance of potential policies related to families. Secondly, because some parents frequently prefer to choose the school they want their child to attend gives us vast space to speculate with factors inside and across schools.

However, these kinds of discussions do not provide us with concrete and fixed answers. Regardless of the extensive education production function introduced in the previous chapter, which points out possible basic components for skill measurement, discovering factors that would really count and defining their range of accountability seems to be a very difficult (if not close to impossible) task. The problem is not in the availability and reliability of data; an increasing amount of international assessment tests of cognitive skills (for example, like the Programme for International Student Assessment, or shortly PISA) generate an incredible amount of data samples, composed from not only formal (or academic) results, but also observations of non-school factors from students questionnaires and school factors from school questionnaires. The nature of obstacles empirical studies face is rather qualitative, meaning that the vast majority of picked indicators are highly correlated with each other and make it a challenge to distinguish and point out causal relationship (*Ibid*). Thus one possible solution may be exploiting of multivariable regression techniques, where correlation of independent variables can be tested.

2.2 Family inputs

The importance of influence of family background on developing cognitive skills and academic results of a student can hardly be understated. Role of families in education has generated little subsequent disagreement in academic literature since it was first mentioned. In other words, family inputs have been considered many times. Nonetheless, it has been a challenge to point out details of what aspects of family are important and relevant to education and how would the causal structure of family effects look (Hanushek, 2002).

Paying close attention to precise measurement and specification of family effects could be extraordinarily expensive if such an approach was to be considered. For example, if mother's education were to be considered as being important in a child's achievement, there is a need for certain data to prove this. Sending all mothers back to school would probably be the best short-run policy in order to get a sample for subsequent research (*Ibid*). On the other hand, the very same logic applied in the long-run policy making process might not sound that absurd. Investing in women's education in developing world countries and studying the outcomes could actually give some notion on the scale of the impact (if there is some).

However, developing policies for longer terms shall not be done spontaneously. Directing long-term policies at family factors, it is extremely important to find out the precise nature of impact of family and know how to distinguish causal relationships. Therefore, an enormous amount of questions arise. For example, is it the mother's education alone that is relevant? Or is it the education of fathers? Or does the number of books at home matter? Or is it some other factor such as wealth, motivating child to be dedicated to studying hard or to like reading, expectations for child's future, and others that truly matter in the analyses? A brief look at the questions reveals that all of the aspects mentioned are interconnected and the latter can be a product of parental education (and vice versa).

Fuchs and Woessmann (2007) argue that the number of books at home can be seen as the major source of information about family education, monetary and social background. Another group of authors (Schütz et al., 2008) showed that the importance of this indicator can be explained as follows. First of all, family income level is very often not included in international assessment tests (PISA as well) and yet can be distantly measured though the number of books quite precisely (more wealthy the family is, more books at home the child possess). Secondly, education standards vary considerably across countries and thus reported level of education does not mean the same thing in all countries, so it limits cross-country comparability. Thirdly, books-at-home variable is far more often stated than, for example, parental education variable.

2.3 School inputs: teacher effect, school effect

It seems to be rather a challenge to decide over the kind of school inputs are there and, moreover, which of them matter. However, measures of the resources going into schools have always made it to the top of discussion topics, simply because budgeting for added expenditures of various sorts raises a series of obvious questions about the necessity of spending more money on these factors. Hanushek (2002) argues that there are three basic categories in which measures of resources devoted to school may be separated.

- The real resources of the classroom (teacher education level and years of experience, and class size or teacher-pupil ratios).
- Financial aggregates of resources (expenditures per each student, teacher salary).
- Measures of other resources in school (administrative inputs, facilities).

However, Hanushek and Woessmann (2010) in their recent study could not find any significant positive effect of financial expenditures. They offer to define school effect using non-financial input measures such as class size, teacher quality, curriculum (and extra curriculum) effect or others (shortage of materials, intensiveness and availability of computers, instruction time).

2.3 The role of peers

Of course, schools are made up of teachers and other personnel, but the major "population" of schools are students. There are many students in the classes; they all interact with each other and it is believed that such interaction creates so called "*peer effect*". The importance of peers has been widely studied in academic literature due to belief that peers play significant role in workplace, education, and behavioural outcomes. An example of extreme peer effect would be bulling; when the bullied person changes their behaviour and most likely to have a significant drop in academic performance.

However, Hanushek (2002) believes that common interpretation, arguing that peers play a more important role in student achievement than other school inputs, has not kept it pace with reality. He suggests that such a belief is a product of omitting or mismeasuring other important school variables. In other words, if we miscalculate individual factors or neglect influences, it may naturally lead to further identification issues, because working with aggregated data that has been mismeasured only leads to reaching wrong conclusion (for example, overstating of peer influences, thus making these influences significant when they are truly not).

Overstatement of peer effect comes from a common belief that peer influences are endogenous or coming from within the system. Thus, we are trapped in a closed system, where only my behaviour affects other students and only their behaviour affects mine. In reality, it is the characteristics of students, such as how motivated or talented or prepared they are, which affect the peers, but the formers come from outside the system (family background). Therefore, this kind of open system challenges us with the very same issue of separating individual effects from peer effects. In this case, our ability to group peers into classes with better learning environment becomes more important and significant from the policy-making standpoint.

The study made by Carrell et. al(2012) faces the same problem trying to estimate the peer effect with emphasis on endogenous sorting and came up with a conclusion that they could not identify the peer effect precisely, due to complexity and richness of human interaction. However, they stated that the presence of middle ability students plays a crucial role for generating positive effect for low achieving students. Zimmer and Toma (2000) found that peer effects are more likely to be important in public rather than in private schools.

3. PISA 2012 AND ESTONIAN RESULTS: DESCRIPTIVE STATISTICS

3.1 The Programme for International Student Assessment

The huge variety of numerous international assessment tests of cognitive skills provides us with an incredible amount of information that can be used for conducting empirical analyses in this field both on the individual level (within the borders of one country) and international level (comparing countries' performance). However, there is one particular test that specifically deserves to get our attention not only for its scale, but only for depth of data it provides. A study conducted by Organisation for Economic Co-operation and Development (OECD) every three years called Programme for International Student Assessment (or PISA) is the world's biggest metric for quality, equity and efficiency in school education. To give a brief overview about the test and data it provides researchers with, from now on in this research paper we will use the PISA 2012 year's results (the most recent ones), with a focus on the Estonian results.

According to the PISA 2012 results overview report, the survey focused on assessing the extent to which 15-year-old students around the world are capable of using what they have learnt in Mathematics, Reading, Science, and other minor areas (like financial literacy). Moreover, the focus is also set on the extent to which students are able to apply that knowledge in unfamiliar situations (both school related and not). As for the scale of the assessment, it can undoubtedly be called worldwide; because it represents more than 80% of the world economy (all 34 OECD member countries and 31 partner countries took part in this survey in 2012). There are about 28 million 15-year-old pupils in the 65 participating countries, which are represented by around 510 000 students of their age, who completed the assessment in 2012.

PISA provides a set of data that can be used not only for assessing academic performance, but also for researching outcome of implemented developmental policies in the past. The survey consists from three main parts: academic assessment and background questionnaire are to fill by students, school questionnaire – by school headmasters (in some countries, there is also a questionnaire for parents, but not in Estonia). Conducting a research about factors that affect cognitive skills results requires just the data of this kind. From author's point of view, it is not really important to assess reliability of the test in terms of measuring pure academic results (we shall assume that these are more or less precise); we do, however, need the rest of the data to find whether and how it influences the end results.

Divided into two big categories, student variables (both personal questions and family background related question) and school variables, the database provides us with answers to not only basic questions like gender, siblings, or number of students in the class, but also to more sophisticated questions. The category with student variables includes information about language spoken at home, possessions (desk, books, and Internet access), education level of parents, fields of interest of students and their motivation level and so on. The other category with school variables includes information about school location, number and qualification of teachers, school material resources (both available items and needed items), extracurricular activities and others.

The data is available in both aggregated (used for comparing results across different countries) and non-aggregated, or raw numbers and is freely accessible online for anyone interested. Vastness of data, however, does not provide us with clear and simple answers. Just like it was discussed above, this data is also not an exception to highly interconnected and highly correlated data, and distinguishing causal relationship may be a difficult challenge to pursue without numerous studies and solid models as a result of the formers. With years to come, periodically collected and evaluated data from PISA assessment shall provide developmental policy makers with real policy guidance.

3.1.1 Estonian PISA 2012 results in comparison with other countries-participants

Before presenting regression models and analysing them, it is important to give some information on how Estonian education system is doing overall compared to the other countries (using PISA 2012 results, of course). According to the PISA 2012 official review (Table 1) Estonia makes it to the top 10 countries in Mathematics, getting in average 521 points (OECD average is only 494 points), outperformed by the East-Asian region, Liechtenstein, Switzerland and the Netherlands. However, in comparison with the leaders it seems that Estonia has managed to produce more equal results, because its shares of the low and top performers are almost equal, whereas in for example Shanghai the share of top performers in more than half of the whole population tested (55,4%).

Table 1. PISA 2012 results: TOP11 performers and neighbouring countries of Estonia.

	Mathematics				Reading		Science	
Country	Mean score in PISA 2012	Share of low achiever in mathematics (Below level 2)	Share of top performers in mathematics (level 5 or 6)	Annualised change in score points	Mean score in PISA 2012	Annualised change in score points	Mean score in PISA 2012	Annualised change in score points
OECD average	494	23	12,6	-0,3	496	0,3	501	0,5
Shanghai	613	3,8	55,4	4,2	570	4,6	580	1,8
Singapore	573	8,3	40	3,8	542	5,4	551	3,3
Hong Kong	561	8,5	33,7	1,3	545	2,3	555	2,1
Taiwan	560	12,8	37,2	1,7	523	4,5	523	-1,5
Korea	554	9,1	30,9	1,1	536	0,9	538	2,6
Macao	538	10,8	24,3	1	509	0,8	521	1,6
Japan	536	11,1	23,7	0,4	538	1,5	547	2,6
Liechtenstein	535	14,1	24,8	0,3	516	1,3	525	0,4
Switzerland	531	12,4	21,4	0,6	509	1	515	0,6
Netherlands	523	14,8	19,3	-1,6	511	-0,1	522	-0,5
Estonia	521	10,5	14,6	0,9	516	2,4	541	1,5
Finland	519	12,3	15,3	-2,8	524	-1,7	545	-3
Poland	518	14,4	16,7	2,6	518	2,8	526	4,6
Denmark	500	16,8	10	-1,8	496	0,1	498	0,4
Latvia	491	19,9	8	0,5	489	1,9	502	2
Norway	489	22,3	9,4	-0,3	504	0,1	495	1,3
Russia	482	24	7,8	1,1	475	1,1	486	1
Lithuania	479	26	8,1	-1,4	477	1,1	496	1,3
Sweden	478	27,1	8	-3,3	483	-2,8	485	-3,1

Sources: (PISA 2012 Results…)

Estonian reading score (516 points) is the weakest amongst the results, giving our country the 12^{th} position in the ranking (still OECD average is 496 points). On the other hand, there is a reason to be proud of Estonian pupils for giving us 6th place in science (541 points, OECD average 501 points). If we were to compare our results to our neighbours' (or OECD in general), then we should be very pleased with them. Despite of failing to outperform Finland in science and Poland in reading, Estonia was able to outperform the other two Baltic Nations, Russia, Sweden, Norway and Denmark in every discipline. Moreover, there are two important things to stress:

a) Estonian results in Mathematics are more equal, producing both low performers and top performers in similar share (compared to Latvia, Lithuania, Norway, Sweden and Russia, where the share of low performers is more than 2 times bigger than the share of top performers).
b) Compared to the PISA 2009 results, Estonia has improved its scores in every discipline more than OECD average (continuing the same trend of improving its results since 2000).

3.2 Descriptive statistics

As was mentioned before, apart from academic results PISA datasets provide us with a huge variety of background information. Choosing which variables to include is a matter of personal judgement, based on theoretical framework, previous empirical work or common sense. Due to the format of this paper and scarcity of space, the author has chosen a limited number of personal, family background related and school variables, presenting the results in Table 2 (next page). In order to give as much extra information about every single variable as possible, all the variables were given a number, every one of which is referring to the list presented below:

1.-3. Variables represent academic results in Math, Reading and Science. The results are presented in so called “*plausible values*”. Plausible values are a representation of the range of abilities that a student might reasonably have (Pisa 2012 Technical Report, 2014). These values are derived from results of a certain student and then adjusted to fit the entire population. When the purpose of assessment is to describe populations, instead of how a single individual doing in this population, using plausible values is preferable (Monseur and Adams, 2009). PISA datasets provide us with 5 plausible values for each of the disciplines. However using averaged values is not methodologically correct (because it provides biased results), thus it is preferable to use only one of the five plausible values. A quite common practise is to use plausible values 1 and this paper is no exception. Please note that using plausible values 1 would results in a slightly different mean values than the official (weighted) results presented in PISA 2012 overview.

Table 2. Summary statistics of Estonian PISA 2012 dataset (only relevant variables).

N	Variable	Abbreviation	Obs	Mean	Std, Dev,	Min	Max
1	Plausible value 1 in Mathematics	pv1math	4779	521,8050	80,2563	238,5964	787,0463
2	Plausible value 1 in Reading	pv1read	4779	517,8044	80,5627	226,050	766,6721
3	Plausible value 1 in Science	pv1scie	4779	543,1917	80,4943	249,9441	820,3469
4	Gender	gender	4779	0,4959	0,5000	0	1
5	How many books at home?	books	4707	3,5037	1,3770	1	6
6	Type of school	sc_type	4779	0,0360	0,1863	0	1
7	Language at home	homelang	4682	0,9436	0,2307	0	1
8	Immigration status	immig	4674	0,9185	0,2737	0	1
9	Highest education level of parents	hisced	4679	4,9109	1,0025	1	6
10	Index of economic, social and cultural status	escs	4727	0,1473	0,7996	-2,24	2,76
11	Wealth	wealth	4740	-0,1774	0,8114	-3,2	2,94
12	Education level of mother (ISCED)	misced	4654	4,6927	1,1038	0	6
13	Education level of father (ISCED)	fisced	4361	4,4602	1,0958	0	6
14	Family structure	famstru	4361	1,8287	0,4281	1	3
15	School location	sc_loc	4779	0,5474	0,4978	0	1
16	Age at <ISCED 1>	age_ 1	4669	6,8743	0,4404	5	8
17	Home Possessions	homepos	4741	0,1206	0,8535	-2,98	3,83
18	Class size	cl_size	4771	4,8235	2,6629	1	9

Sources: (PISA 2012 Database)

4. Gender – a binary (or dummy) variable, where 0 stands for “Female” and 1 stands for “Male”.
5. Students were asked to approximately estimate the number of books they possess at home. Possible answers: 1 = "0-10 books", 2 = "11-25 books", 3 = "26-100 books", 4 = "101-200 books", 5 = "201-500 books", 6 = "More than 500 books".

6. Type of school: 0 = "Public", 1 = "Private" (from school questionnaire).
7. Language at home: 0 = "Any other language", 1 = "Estonian".
8. Immigration status: 0 = "First and second generation immigrants", 1 = "Native".
9. Highest education level of parents: 0 = "None", 1 = "ISCED 1", 2 = "ISCED 2", 3 = "ISCED 3B, C", 4 = "ISCED 3A, ISCED 4", 5 = "ISCED 5B", 6 = "ISCED 5A, 6". Applying these criteria to Estonian system is a bit of a challenge, because in PISA 2012 the dataset provides us with ISCED 1997 standard, which is less precise than its next edition ISCED 2011. However, being utterly precise is not crucially important. Level 3 and 4 would be equal to academic secondary and professional secondary education. Starting from level 5 we would be dealing with higher education. (ISCED, 1997)
10. The PISA index of economic, social and cultural status (ESCS) is derived from highest parental education (in number of years of education according to ISCED classification), highest parental occupation (HISEI scores), and number of home possessions including books in the home (Pisa Data Analysis Manual, 2009).
11. The PISA index of family wealth possession derived from questions like "Do you have a room on your own?", "A link to the Internet", and other questions related to things at home (cars, cellar phones etc.). (Pisa 2012 Technical Report, 2014)
12. -13. Education level of mother (ISCED) and Education level of father (ISCED): 0 = "None", 1 = "ISCED 1", 2 = "ISCED 2", 3 = "ISCED 3B, C", 4 = "ISCED 3A, ISCED 4", 5 = "ISCED 5B", 6 = "ISCED 5A, 6". Identical to variable described in 9 (above).
14. Family structure: 1 = "Single parent (natural or otherwise)", 2 = "Two parents (natural or otherwise)", 3 = "Other".
15. School location: 0 = "Village or small town" (fewer than 15 000 people), 1 = "Town or city" (15 000 to about 1 000 000 people).
16. Age at <ISCED 1>: Pupils were ask to tell how old they were when they enrolled to school (years).
17. The index of household possessions/assets as an indicator of family wealth.
18. Class size: 1 = "15 students or lower", 2 = "16-20 students", 3 = "21-25 students", 4 = "26-30 students", 5 = "31-35 students", 6 = "36-40 students", 7 = "41-45 students", 8= "46-50 students", 9 = "More than 50 students".

3.2.1 Differences in academic results by gender

According to the PISA 2012 dataset, there were in total 4779 participating students from Estonia, male participants 2370 and female participants 2409, resulting in almost equal representation of boys and girls. In order to give a better illustration of how boys and girls performed academically compared to each other, the author used Figure 2 (using averaged plausible values 1). Girls outperform boys in reading by almost 45 points (and slightly in science, which is also believed connected to one's reading abilities) and there is quite a lot of evidence from other countries that girls usually do better at reading than boys. It is difficult to say whether girls read more than boys, but as for numbers of books at home the result fall into the same categories (slightly overweighed by girls, stating to have around 26-100 books at home for 0.18 times more – which is rather insignificant).

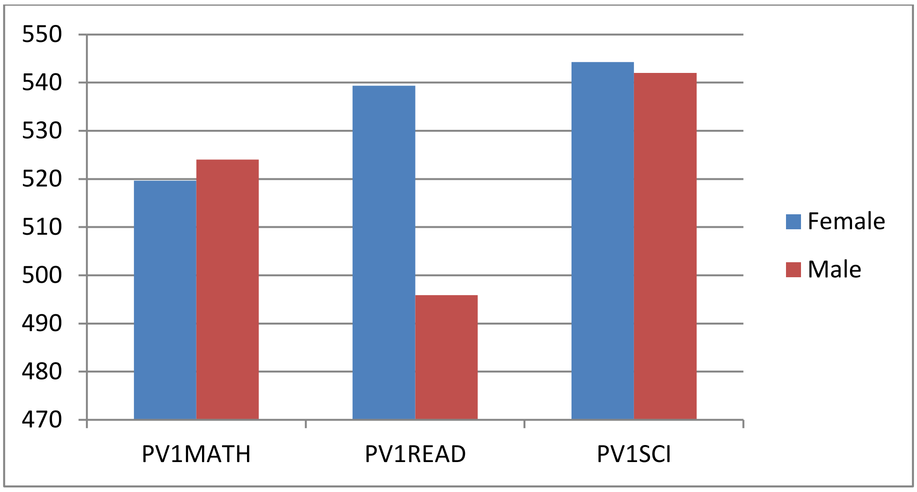

Figure 2. Estonian PISA 2012 results by gender in Mathematics, Reading and Science (averaged Plausible values 1).
Sources: (Table 2)

However, boys outperform girls in Mathematics by 4 points and this trend becomes more obvious throughout countries. There are some attempts to explain this phenomenon by gender differences in cognitive style. In other words, it is possible to explain why boys perform better than girls in mathematics by differences in ways of thinking (Wholistic-Analytic vs Verbal-Imagery cognitive styles) and design lessons differently for boys and girls (Cognitive..., 2013). Although boys in Estonia outperform girls in Mathematics, the gap is not that big and we may conclude that this results from more individual approach practiced by Math teachers in Estonia.

3.2.2 Differences in academic results by type of school

System of schools giving basic education ("üldhariduskool") in Estonia can be distinguished into three categories: state schools ("riigi omaduses"), local schools ("munitsipaalkoolid") and private schools ("erakoolid"). PISA dataset provides us with only two categories: public and private. This variable is coming from school questionnaire and filled in by school representatives. Both state schools and local schools fall into the first category of "public" schools and all private schools are marked as "private". Division into these two categories has nothing to do with who is financing schools, but who is the owner.

There were 545 schools ("üldhariduskool") across Estonia in 2014 (Haridus…) and almost half of them were tested during PISA 2012, with number of schools observed equal to 206. Private schools are not that popular in Estonia (in total about 20 schools), resulting in 9 private schools tested. Thus we can assume that about 98% of schools in Estonia are public. There is no surprise that private schools do better in all three disciplines (see figure 3). However, only 3,6% of all tested students are from private schools and their results are insignificant compared to the rest of the population.

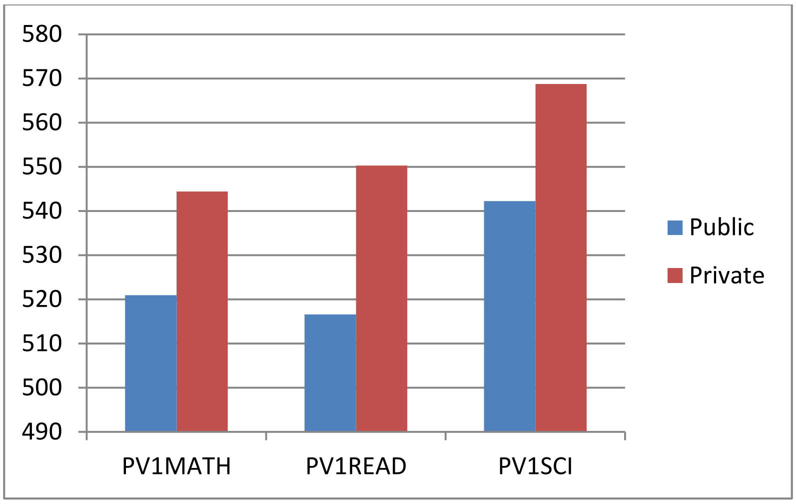

Figure 3. Estonian PISA 2012 results by type of school in Mathematics, Reading and Science (averaged Plausible values 1).
Sources: (Table 2)

3.2.4 Differences in academic results in Estonian and Russian schools (in Estonia)

There is quite a difference in how students in Estonian schools and Russian schools (in Estonia) perform. Students of Estonian schools outperform their “colleagues” from Russian schools in all three subjects (see Figure 4). Estonian PISA 2012 results overall are better than OECD average (see Table 1), whereas the results in Reading of Russian students from Estonia are around 9 points less than the OECD average. However, students from Russian schools in Estonia perform a lot better than Russian students from Russia, whereas the formers outperform the latters in all three subjects (being especially skilful according to the scores in Science).

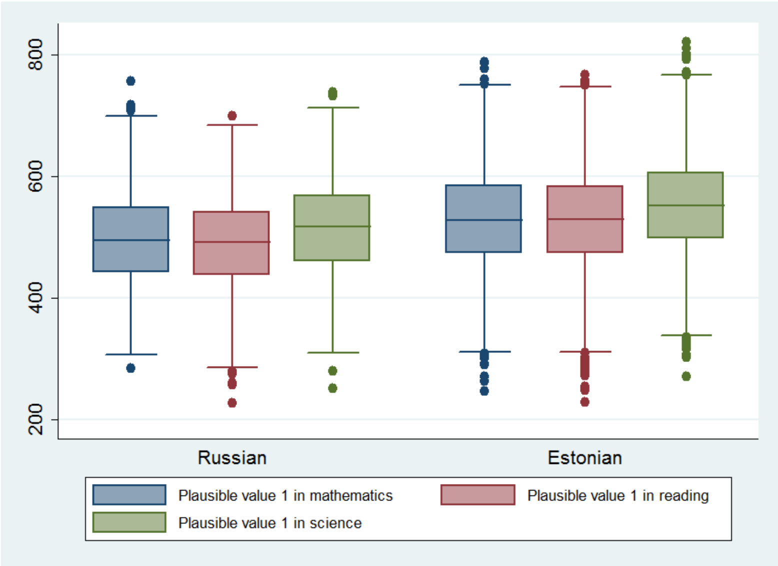

Figure 4. Estonian PISA 2012 results in Estonian and Russian schools in Mathematics, Reading and Science (averaged Plausible values 1).
Sources: (Table 2)

Two possible explanations of such trend can be noted:

1. Student from Russian schools in Estonia have to learn official language (Estonian language) from grade one and may be lacking studying hours in other subjects, such as Maths and Science. Score in Reading shows how deeply can students understand texts in their mother tongue (in this case, Russian) and lower scores in Reading may be resulted also in incorrect translation.

2. Due to (generally) lacking skills in speaking Estonian language amongst the teachers from Russian schools in Estonia, there is a possibility of new methodologies, techniques and innovation not reaching to the teachers provided through different education programmes and camps from the government (Ministry of Education, etc).

3.2.4 Analysing academic results and their distribution

Taking into account that PISA dataset provides us with three academic results, to simplify our task it is necessary to choose only one variable as dependent. Figure 5 (upper graphs) provides us with some significant evidence that academic results are highly correlated compared between each other (see correlation matrix, Table 3). Results of this matrix man interpreted in a way that any particular student performs in a similar manner in all three subjects: top performers are good in all disciplines, low performers – in none. Thus taking any score would not affect the end results in a significant manner. Moreover, as it was discussed in 3.2, using average of plausible values would produce biased results, so taking only one score can also be reasoned with methodological standpoint.

Table 3. Correlation matrix of plausible values 1: Math vs Reading vs Science

	PV1MATH	PV1READ	PV1SCIE
PV1MATH	1,0000		
PV1READ	0,8367	1,0000	
PV1SCIE	0,8848	0,8516	1,0000

Sources: (Table 2)

Finally, in order to make sure that taking any of the PISA academic results as depended variables would not produce any biased estimators, figuring out whether the results distribute normally. Figure 5 (bottom graphs) shows that distributions of plausible values 1 in all three disciplines are close to normal and thus the risk of getting biased estimators is not relevant. Therefore, all of three are suitable for further analysis, and taking only one result would still produce unbiased estimators and correct end results.

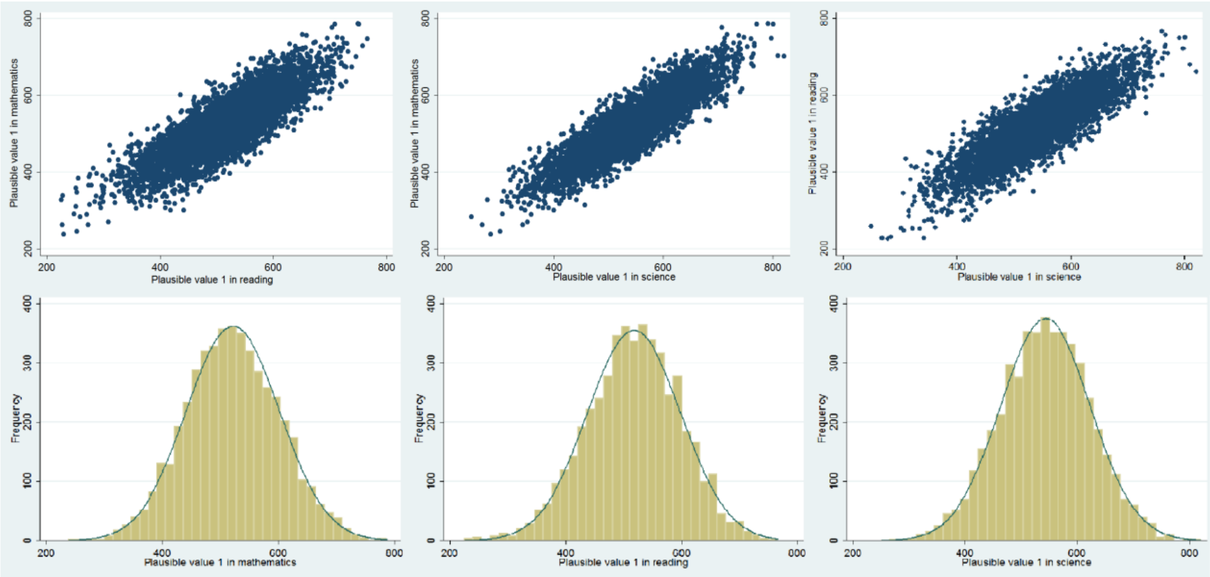

Figure 5. Upper: correlation scatters (of plausible values 1) Math vs Reading, Math vs Science, Reading vs Science. Bottom: Distribution histograms by Math, Reading and Science (plausible values 1).

Sources: (Table 2)

To conclude, deciding upon which of the three scores provided to use as the dependent variable is up to an author. In this paper, it was decided that using plausible values 1 in Mathematics would end in better models, providing better insights into cognitive skills. Furthermore, the author truly believes that using scores in Math would provide better results just because the score itself is less connected to one’s language abilities (correlation between Math and Reading score is the least, see table 3) since language ability and reading skills are difficult to measure across countries.

4. EMPIRICAL ANALYSIS AND RESULTS

4.1 Main objectives and education production function

The main objective is to estimate education production function based on Estonian results in PISA 2012. Using data provided in Table 2, we can compose different regression functions that can be later analysed. However, there are not many options for presenting these functions in generalised version and one of the options goes as follows:

$$\begin{aligned}\log pv1math_{is} \\ &= \alpha + \beta_n \sum_{n=1}^{4} personal\ characteristics_{is} \\ &+ \gamma_m \sum_{m=1}^{8} family\ background_{is} \\ &+ \delta_p \sum_{p=1}^{3} school\ characteristics_{is}\end{aligned} \tag{2}$$

where

- Pv1math - indicates math test result of a single individual;
- i – an individual student from certain school s;
- personal variables – gender, homelang, immig, age-1;
- family background – books, hisced, escs, wealth, misced, hisced, famstu, homepos;
- school characteristics – sc_type, sc_location, class_size.

I applied log-linear estimation technique in generalised version of education production function (2). In order to make interpretation of data easier, we took the natural logarithm of the plausible values 1 in Mathematics. Instead of talking about cause on the actual amount of score points, a log-linear model provides us with an opportunity to analyse any changes in

Math scores in percentages. Thus the effect sizes in regression Table 4 should be interpreted as average percentage point changes in the case phenomenon is present

Due to length restrictions of this paper, we are focusing mainly on analysing family background effect (FBE). Therefore, we hypothesise that FBE constitutes a major and statistically significant effect on Estonian PISA 2012 results in Math.

4.2 Log-linear regression models

Generalised education production function (see Equation 2) provides us with a great tool for combining various characteristics together and thus makes it possible to add and delete non-significant variables till every kind of impact on the dependent variable is explained. Based on both previously mentioned theoretical insights (see parts 1 and 2) and descriptive statistics (see part 3), we have constructed 8 different log-linear regression models (results find in Table 4). In all modules school cluster robust standard errors are applied in the estimation, latter treats the problem of unobservable homogeneity of the students coming from the same school. The effects of the included variables can be interpreted as follows:

- *Personal variables*:
  1) Gender – part 3.2.1 tells us that boys on average outperform girl in Mathematics and throughout all of the 8 models gender has significant impact on the Math scores. Being a boy means that you get around 2% extra in Math tests independently on model specification.
  2) Immigration status – being a native Estonian gives you statistically significant advantage of 5% extra points. This is actually a quite positive result for Estonia and once again strong evidence that Estonian system of education produces equal outcomes for both Estonian native and non-native population. Therefore, the gap between natives and non-natives in Estonia is quite marginal. Also literature has shown that this gap is also closing if we compare similar analysis based on PISA 2009 and 2012 data. There is also some empirical evidence that the official language does not really have a huge impact in the private sector, and at the upper end of the income distribution (Toomet, 2010).

3) Age at <ISCED 1> - not surprisingly enrolling in primary school earlier than other peers provides better results in PISA (simply because the length of education obtained in years is bigger). Varying from age of 5 to 8, entering school one year later results in losing 3% of PISA scores.

- *Family background effect*:

4) Number of books at home – having more books at home results in better Math scores. The impact varies from 3 to 4%, diminishing as new variables enter the equation, because number of books as a variable is used in some indices (for example, wealth). In current analyses I treat books as a linear variable, meaning that each category will produce same effect size. However, this linearity assumption may be contested.

5) Parental education (hisced, misced, ficed) – just as previously stated academic evidence suggested father's level of education has no statistically significant effect on the scores. On the other hand, mother's level of education is significant, with surprisingly negative effect which is however marginal (less than minus 1%). The minus sign before the coefficient appears due to correlation with index of economic, social and cultural status (escs), whereas the latter is derived from the years of parental education and strongly connected to the level of education of parents (PISA Data Analysis Manual, 2009).

Table 4. Regressions: Log-linear regression models with school robust standard errors

Variable	**Model1**	**Model2**	**Model3**	**Model4**	**Model5**	**Model6**	**Model7**	**Model8**
Y	log_m_PV1	log_m_PV1	log_m_PV1	log_m_PV1	log_m_PV1	log_m_PV1	log_m_PV1	log_m_PV1
gender	0.0154**	0.0178***	0.0179***	0.0196***	0.0188***	0.0202***	0.0203***	0.0199***
	(0.00492)	(0.00499)	(0.00491)	(0.00500)	(0.00524)	(0.00519)	(0.00518)	(0.00488)
books	0.0433***	0.0430***	0.0331***	0.0338***	0.0328***	0.0327***	0.0328***	0.0336***
	(0.00196)	(0.00189)	(0.00173)	(0.00183)	(0.00188)	(0.00249)	(0.00248)	(0.00170)
Sc_type	0.0192	0.0145	0.00847	0.0144	0.0145	0.0157	0.0154	
	(0.0289)	(0.0288)	(0.0269)	(0.0270)	(0.0234)	(0.0234)	(0.0236)	
homelang		0.0210	0.0192	0.0250*	0.0269*	0.0279*	0.0277*	0.0207
		(0.0119)	(0.0112)	(0.0121)	(0.0127)	(0.0131)	(0.0130)	(0.0126)
immig		0.0520***	0.0481***	0.0497***	0.0541***	0.0558***	0.0559***	0.0525***
		(0.00970)	(0.00893)	(0.00852)	(0.00835)	(0.00846)	(0.00844)	(0.00882)
hisced			-0.0168***					
			(0.00392)					
escs			0.0637***	0.0552***	0.0533***	0.0512***	0.0511***	0.0496***
			(0.00608)	(0.00540)	(0.00555)	(0.00579)	(0.00581)	(0.00513)
wealth			-0.0265***	-0.0245***	-0.0238***	-0.0222**	-0.0221**	-0.0213***

			(0.00359)	(0.00349)	(0.00359)	(0.00736)	(0.00734)	(0.00340)
misced				-0.00756**	-0.00853**	-0.00737*	-0.00737*	-0.00743*
				(0.00287)	(0.00291)	(0.00292)	(0.00292)	(0.00291)
fisced				-0.00234	-0.00287	-0.00200	-0.00200	
				(0.00261)	(0.00251)	(0.00248)	(0.00248)	
famstru					-0.00411	-0.00450	-0.00452	
					(0.00603)	(0.00603)	(0.00602)	
sc_loc					0.0143	0.0120	0.0117	0.0104
					(0.00733)	(0.00727)	(0.00738)	(0.00719)
age_1						-0.0298***	-0.0296***	-0.0297***
						(0.00488)	(0.00490)	(0.00499)
homepos						-0.000384	-0.000508	
						(0.00825)	(0.00823)	
class_size							0.0000742	
							(0.000280)	
_cons	6.087***	6.021***	6.130***	6.084***	6.094***	6.291***	6.288***	6.278***
	(0.00711)	(0.0134)	(0.0214)	(0.0207)	(0.0270)	(0.0417)	(0.0437)	(0.0380)
N	4707	4588	4532	4205	3922	3864	3864	4443
R^2	0.146	0.158	0.194	0.195	0.194	0.203	0.203	0.199

Sources: (PISA 2012 Database)

Comment: Standard errors in parentheses * p<0.05, ** p<0.01, *** p<0.001

6) The PISA index of economic, social and cultural status (escs) – has a significant impact on the end results in Math, varying from 5 to 6,4%. The index is derived from three other indices and one of them is "homepos" (home possessions). One of the data used for "homepos" index is the number of books at home. Therefore, escs provides biased result and gains its weight from the "books" variable.
7) Wealth – the PISA index of wealth does not contain the "books" variable (PISA Data Analysis Manual, 2009), but covers pretty much majority of questions used in computing "homepos" index and thus connected to escs. Moreover, being a biased and statistically significant variable, it produces negative effect of only 2% and goes against majority of obtained academic evidence.

- *School characteristics:* none of the variables is statistically significant. This brings us back to the points discussed in part 3. Type of school does not really matter, if we control for family background and personal characteristics, it indicates that private schools do not provide significantly better results and their portion in the whole education system is marginal. If school is located in town or city, it results in only 1% better results in Maths, but still the effect is not statistically significant. The size of

Estonia and cooperation amongst schools and within the system seems to provide more or less equal results.

4.2.1 Final specification of the model: statistical post-estimation

In this part, we would like to focus on the Model 8 (see Table 4). The model itself contains the biggest number of significant variables and cleaned-up from the majority of non-significant characteristics. Nonetheless, our hopes to have statistically significant results for both language at home (variable "homelang") and school location (variable "sc_lc") did not fulfil and both characteristics remained statistically non-significant. The model's R-squared is equal to 19,9%, thus this model provides us with capability to explain about 1/5 of all variations (which is a very good result, when we are dealing with micro data). The major effects remain the same as explained before (see part 4.2).

To better illustrate how well the population is covered by this log-linear model, a graph of the residuals against the fitted values is provided (see Figure 6 on the next page). The graph provides us important insights into the model and its fit. In a well-fitted model that shall be no pattern to the residuals plotted against the fitted values – something not true for this model. Ignoring the outliers, we still can notice that the dots tend to shape an ellipse-like figure. This suggests that our assumption that Math score is linear to dependent variables is being violated. Any pattern indicates a violation of the least-squares assumptions.

4.3 Drawbacks of the models and suggestions for further analysis

Trying to interpret the effects in our models has shown that there are significant drawbacks in them. In this part, we will try to point out possible drawbacks in our assumptions and provide with some suggestions for further analysis.

Some of the PISA indices should not be used together because some of the questions these indices are derived from are the same. For example, taking our log-linear regression model 8 and creating a correlation matrix provides us with such evidence (see Table 5 on the next page). Mother's level of education is one of the questions used to compose the escs index and they do correlate quite strongly (66%). Same goes for the wealth index compared to the same escs index, resulting in correlation equal to 55%. This suggests that using this kind of

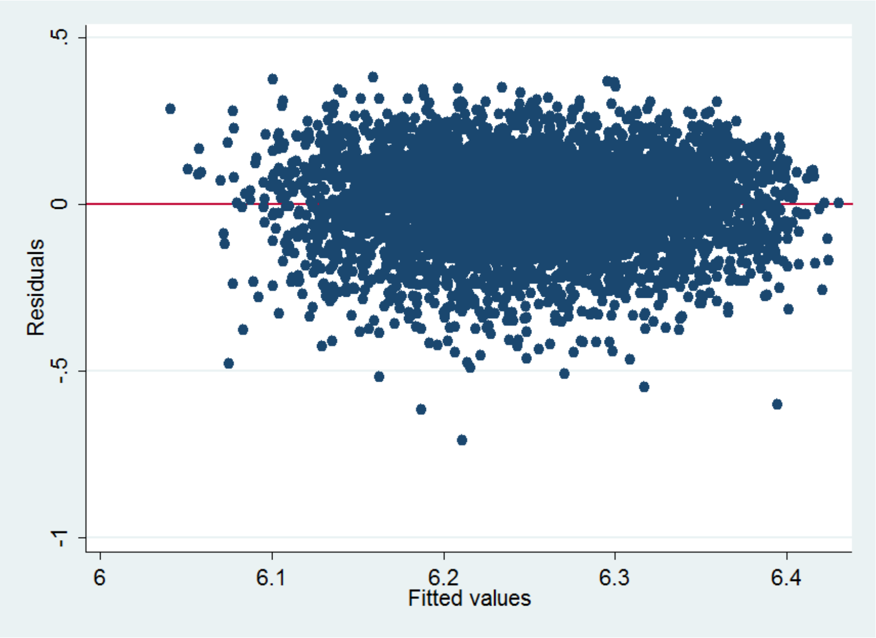

Figure 6. Log-linear regression model 8 on a graph of the residuals against the fitted values. Sources: (Table 4)

indices is not reasonable and one should whether to compose their own indices (of course, using distributional techniques to make these indices relevant for the entire population, since not every student answers to all the questions correctly), or leaving out variables like misced used in the indices. The latter option may results in making it difficult to interpret results and see which of the variables is relevant rather than the index itself.

Table 5: Correlation matrix of the log-linear regression model 8

	gender	books	homelang	immig	escs	misced	wealth	sc_lc	age-1
gender	1,0000								
books	-0,0626	1,0000							
homelang	0,0219	0,0347	1,0000						
immig	-0,0349	0,0046	0,2065	1,0000					
escs	0,0429	0,4167	0,0283	0,0103	1,0000				
misced	0,0249	0,2579	-0,0073	-0,0412	0,6546	1,0000			
wealth	0,1069	0,1245	0,0116	0,0126	0,5453	0,1691	1,0000		
sc_lc	0,0105	0,1141	-0,0373	-0,1040	0,2345	0,2356	0,0721	1,0000	
age-1	0,0474	-0,0423	0,0328	0,0563	-0,0403	-0,0470	0,0045	-0,0683	1,0000

Source: (Table 4)

Furthermore, before choosing whether to use indices or not, it is important to understand what kind of variables are really relevant. Deciding upon the variables to include into a model is a very difficult process, simply because later on it offers very strange interpretations. As an example, the number of books at home is not only a statistically significant variable, but also quite popular input to be used in this kind of empirical work. However, does it really make sense that more books you have at home, more PISA points you are likely to get. Shall one simply go to a bookstore and buy as many books as possible? Or there is actually another input that matters more and has got remote influence on the number of books as well. Probably yes, but is it wealth itself (books are quite expensive and can be used as a direct indicator of wealth) or one's parents behind this wealth (their level of education, their dedication to child's future and so on) that matter? Finally, do the chosen variables have linear effect on cognitive skills of a child (Figure 6 clearly suggests that log-linear equation provides us with restrained results)?

Due to specific (empirical) nature of education economics, the results and conclusions of this paper are only applicable to Estonian PISA 2012 results and may not provide same results in any other country. However, empirical analysis of this kind is very important for providing insights into a country's system of education and creation of cognitive skills in that particular country, that can be later used as ideas for interpreting data in other countries as well.

CONCLUSION

There has been no clear evidence on the tight, confirmed causal relationship between cognitive skills and economic growth. There is some evidence that greater schooling enrolment in 1960 consistent with an extra year of attainment could be associated with only about 0,30% faster growth in the next thirty years. However, it is clearly not possible to claim schooling be the cause of growth.

On the other hand, our ability to explain variations in long-term growth among countries can be improved drastically just by measuring differences in education achievements more accurately. If cognitive skills from international tests of Math and Science are taken into account and added into the growth model, we get a slight positive trend to the picture. Models that exclude cognitive skills from their account and use only years of schooling as a measure of economic growth, shall account for about three times wider variations of the economic outputs.

Using the extensive education production function with the results of international assessment tests like PISA (Programme for International Student Assessment), we can actually capture all the variations in the knowledge and ability that schools produce and then use as a measurement of subsequent economic success, incorporate skills from any source - families, schools, and ability into the model, and study differences in performance among students with varying quality of education (even if the years of schooling is the same).

The irrelevance of comparing students merely on their performance at school stresses obvious necessity to include various factors outside schools into any analyses of cognitive skills. Family inputs can be measured via the number of books at home since it can be seen as the major source of information about family education, monetary and social background. School effect can be better defined with non-financial input measures such as class size, teacher quality, and curriculum effect or other. Peer effect is very difficult to catch due to complexity and richness of human interaction, but still can be measured in case of endogenous sorting. All the factors are correlated and thus a complex multivariable model can explain creation of cognitive skills better than studying these factors one by one.

Luckily, PISA datasets do provide us with basically all information needed. In this paper, we focused on Estonian PISA 2012 results and tried to show that they are significantly affected by family background effect. The history of PISA is not that long and Estonia has succeeded in not only outperforming most of the participating countries, but also managed to gradually improve its results in all three disciplines (Math, Reading, and Science). Therefore, bringing Estonia is an example was meant to find some special insights into building up cognitive skills. However, due to specific (empirical) nature of education economics, the results and conclusions of this paper are only applicable to Estonian PISA 2012 results and may not provide same results in any other country.

Based on theoretical framework discussed in chapters 1 and 2, a log-linear regression model was designed to include personal variables, family background effect and school characteristics. The dependent variable is PISA plausible value 1 in Mathematics, which was chosen with an assumption to minimise language impact on the results (simply because literacy is difficult to compare throughout different countries). Since interpretation of the results may be a difficult task and go way beyond the format of this paper, the natural logarithm of the dependent variable was taken, providing us with an opportunity to interpret the effects in percentages. Observed effects can be summarised as follows:

- Personal variables: Boys on average outperform girl in Mathematics and get around 2% extra in Math tests. Being a native Estonian gives you statistically significant advantage of only 5% extra points. The impact of one's home language is statistically non-significant at all. This is actually a quite positive result for Estonia and therefore the gap between natives and non-natives in Estonia is quite marginal. Enrolling in primary school earlier than other peers provides better results in PISA. Varying from age of 5 to 8, entering school one year later results in losing 3% of PISA scores.
- Family background effect: Possessing more books at home results in better Math scores. The impact varies from 3 to 4%, diminishing as new variables enter the equation, because number of books as a variable is used in some indices (for example, wealth). Parental education does matter, but only mother's level of education is statistically significant (effect is less than minus 1%). Stated minus sign refers that there some co-variable characteristics and the effect seems to be biased.
- School characteristics: Type of school does not really matter, because private schools do not provide significantly better results and their portion in the whole education

system is marginal. School location results in only 1% better results in Maths, but still the effect is not statistically significant. Class size is also non-significant.

On the other hand, there are some significant problems discovered while performing this empirical analysis. Some of the PISA indices should not be used together because some of the questions these indices are derived from are the same. Moreover, it seems that log-linear regression model is not the best equation for explaining variations in PISA scores. Some of the variables due to their categorical nature have nonlinear effect on dependent variable, thus in estimating average effect it could be beneficial to indicate each category separately by estimating their marginal effects. Finally, deciding upon the variables to include into a model is a process where case specificities may distort the knowledge driven from the literature. For example, the “books” variable is very popular in empirical analysis of cognitive skills, but is it true that more books at home you have, higher your PISA score would be? Shall one just go to a bookstore and buy as many books as possible? Thus effect sizes and their significance cannot be taken as a causal interference and interpreted as causality; rather this paper derives partial marginal effect or partial correlations in explaining students’ scores in PISA mathematics test.

REFERENCES

Arnup, J.L., Murrihy, C., Roodenburg, J., McLean, L.A. (2013). Cognitive style and gender differences in children's mathematics achievement. Education Studies, 39(3), 355–368.

Barro, R. J. (2001). Human capital and growth. American Economic Review, 91(2), 12-17.

Bils, M., Klenow, P. J. (2000). Does schooling cause growth? American Economic Review, 90(5), 1160-1183.

Carrell, S. E., Sacerdote, B. I., West, J. E. (2013). From Natural Variation to Optimal Policy? The Importance of Endogenous Peer Group Formation. Econometrica, 81(3), 855–882.

Ciccone, A., Papaioannou, E. (2009). Human capital, the structure of production, and growth. Review of Economics and Statistics, 91(1), 66-82.

Fuchs, T., Woessmann, L. (2007). What Accounts for International Differences in Student Performance? A Re-Examination Using PISA Data. Empirical Economics, 32(2), 433-462.

Hanushek, E. A., Woessmann, L. (2012). Do better schools lead to more growth? Cognitive skills, economic outcomes, and causation. Journal of Economic Growth, 17, 267-321.

Hanushek, E. A. (2002). Publicly provided education. In A. J. Aurbach & M. Feldstein (Eds.), Handbook of Public Economics. (pp. 2045-2141). Amsterdam: Elsevier.

Hanushek, E. A., Woessmann, L. (2010). The Economics of International differences in education achievement. NBER Working Paper, No. 15949 (April). Cambridge MA: NBER Working paper series.

Hanushek, E. A., Woessmann, L. (2008). The role of cognitive skills in economic development. Journal of Economic Literature, 46(3), 607-668.

Haridus- ja Teadusministeerium. 2014/2015 õppeaasta numbriinfo (Raport). [WWW] https://www.hm.ee/sites/default/files/uue_oppeaasta_numbriinfo_0.doc (25.05.2015)

International Standard Classification of Education (ISCED) 1997. [WWW] http://www.unesco.org/education/information/nfsunesco/doc/isced_1997.htm (24.05.2015)

Monseur, C., Adams, R. (2009). Plausible Values: How to Deal with Their Limitations. Journal of Applied Measurement, 10(3).

PISA 2012 Database. [WWW] http://pisa2012.acer.edu.au/ (23.05.2015)

PISA 2012 Results in Focus: What 15-year-olds know and what they can do with what they know (2012). / OECD Report. (http://www.oecd.org/pisa/keyfindings/pisa-2012-results-overview.pdf)

PISA 2012 Technical Report (2014). OECD Report. (http://www.oecd.org/pisa/pisaproducts/PISA-2012-technical-report-final.pdf)

PISA Data Analysis Manual: SPSS Second Edition (2009). OECD Report. (http://browse.oecdbookshop.org/oecd/pdfs/free/9809031e.pdf)

Toomet, O.S., Meriküll, J., (2010) Language Skills and Social Integration: Ethnic Disparities in Bilingual Economy. Paper 29. [http://opensiuc.lib.siu.edu/pnconfs_2010/29]

Schütz, G., Ursprung, H. W., Woessmann, L. (2008). Education Policy and Equality of Opportunity. Kyklos, 61(2), 279-308.

Zimmer, R.W., Toma, E.F. (2000). Peer effects in private and public schools across countries. Journal of Policy Analysis and Management, 19(1), 75−92.

KOKKUVÕTE

KOGNITIIVSETE OSKUSTE MÕÕTMINE EESTIS PISA 2012 ANDMETEL

Alexey Volkov

Investeeringud haridusse ja inimkapitali on juba rohkem kui 30 aastat olnud päris terava kriitika all, kuna nende efektiivsus ja tulemuslikkus pikaajalise majanduskasvu tagamises ei ole häid tulemusi näidanud. Erinevad teoreetilised arengumudelid on korduvalt rõhutanud inimakipitali olulisust kui peamist majanduskasvu mootorit, aga paraku, arengustrateeriate väljatöötamise käigus ja nende tulemustele toetudes ei suudetud seda tõestada. Keskne probleem seisneb sellest, et meie arusaam inikapitali ja kognitiivsete oskuste tekkimisest ja mõõtmisest on olnud üsna piiratud. Siiski, mitmed empiirilised uuringud on näidanud et meie oskus inimkapitali mõõta paraneb oluliselt siis, kui riikidevahelised erinevused kognitiivsetes oskustes on mõõdetud täpsemate metoodikate alusel (näiteks, rahvusvaheliste testide alusel).

Kui kognitiivsed oskused on väljendatud rahvusvaheliste matemaatika ja loodusteaduste testitulemuste alusel ja siis lisatud majanduskasvu mudelisse, siis mudelite selgitusvõime oluliselt paraneb. Olen näidanud, et selline mudel, kuhu ei ole kognitiivseid oskusi kaasatud ja mis kasutab haridustaseme mõõtmiseks ainult saadud hariduse pikkust (aastates), annab majanduskasvu selgitamisel kolm korda suurema variabiilsuse.

Hariduslik tootmisfunktsiooni kasutamine koos rahvusvaheliste testitulemustega, nagu näiteks PISA (Programme for International Student Assessment), võimaldab meil kasutada indiviidi tasemel testi tulemusi ja analüüsida erinevate efektide (ehk muutujate) mõju. Peamiselt kasutatakse analüüsil sõltuvaid muutujaid, mida on võimalik grupeerida nn. isiklikeks (sugu, kodune keel jne), peretaustaks (vanemate haridus, varanduslik seis jne) ja ka kooli võimekuseks (omandivorm, ressursid jne). Mitme-muutujaga regressioonivõrrand

võimaldab hinnata kovarieeruvate muutujate efekte ehk aitab mõista, kuidas kognitiivsed oskused tekivad ning mis neid mõjutab. Viimane võimaldab hiljem jõuda ka majandusedu ja majanduskasvu jäljele.

Õnneks sisalduvad PISA andmebaasides peaaegu kõik selleks analüüsiks vajalikud muutujad. Selles töös keskendusime PISA 2012. aasta tulemustele Eestis ja üritasime näidata, et PISA testide tulemused on oluliselt mõjutatud peretausta efektist (*family background effect*). PISA ajalugu ei ole väga pikk, aga Eesti on juba korduvalt võtnud sellest osa ning on mitte ainult näidanud suurepäraseid tulemusi võrreldes teiste riikidega, kui ka aastast aastasse oluliselt parandanud tulemusi kõikides valdkondades (matemaatika, lugemisoskus ja teadus) . Seega Eesti andmete kasutamine on heaks näiteks kognitiivsete oskuste akkumuleerimisest ja tekitamisest. Kahjuks, haridusökonoomika spetsiifika eeldab, et iga teostatud uuringu tulemused ei ole universaalsed ja on seotud just konkreetse impiirilise analüüsiga (selle analüüsi puhul PISA 2012. aasta tulemused just Eestis) ning ei pruugi teistes riikides samu tulemusi näidata.

Töö käigus on koostatud mitme muutuja log-lineaarne regressiooni mudel, kus indiviidi tasemel on hinnatud hariduslikku tootmisfunktsiooni. Mudelis on sõltuvaks muutujaks PISA matemaatika testi tulemus ja sõltumatute muutujatena on kaasatud individuaalsed omadused, peretausta efekt ja kooli muutujad. Sõltuvaks muutujaks on valitud matemaatika „võimalikud" väärtused 1 (*plausible values 1 in Mathematics*), mille valik on põhjendatud sellega, et matemaatika oskus on seotud inimese keele võimetega kõige vähem (keeleoskuste hindamine riikide lõikes on üsna problemaatiline). Regressiooni mudeli tulemuste lihtsamaks interpreteerimiseks oli otsustatud võtta sõltuvast muutujast naturaalne logaritm, seega efektide mõju avaldub protsentides. Uuritud efektide kokkuvõte esitatud järgnevalt:

• Individuaalsed omadused: Poiste tulemused matemaatikas on keskmiselt paremad ning erinevus on 2%. Kui sa ei tunne ennast immigrandina, siis sinu matemaatika testitulemused on 5% paremad. Samas aga kodukeel ei ole statistiliselt üldse oluline. See on tegelikult väga positiivne tulemus ja see näitab, rahvusest tulenevad erinevused on väga väiksed. Kui laps hakkab teistega võrreldes koolis varem käima, siis tema tulemus on iga aastaga paraneb 3% , st et kognitiivsed võimed kasvavad teatud vanusepiires 3% ehk tegemist on nn klassiefektiga.

• Peretausta efekt: Kui lapsel on kodus palju raamatuid, siis tema matemaatika tulemused on paremad. Efekti suurus varieerub 3 ja 4% vahel ning see suurus väheneb siis kui mudelisse lisatakse teisted muutujad (kuna raamatute arv on kasutatud mõnede indeksite arvutamisel, näiteks „wealth“ ja „escs“). Vanemate haridus ei mängi olulist rolli, ainult ema haridustase on statistiliselt oluline, aga selle efekti suurus on marginaalne ja oodatust erinev.

• Kooli muutujad: Tulemused näitavad, et kooli omandivorm ei ole Eestis oluline, sest erakoolid ei tooda statistiliselt paremaid tulemusi ning nende osakaal haridussüsteemis on marginaalne. Oluline on ka see, et kooli geograafiline asukoht ei mõjuta tulemusi. Matemaatika tulemused paranevad ainult 1% protsendi võrra, kui kool asub linnas, aga efekt tervikuna ei ole statistiliselt oluline. Sama lugu klassi suurusega – ei ole statistiliselt oluline.

Paraku, ei ole koostatud mudelid ideaalsed ning impiirilise analüüsi teostamisel oleme tuvastanud mõned kitsaskohad. Mõnesid PISA indekseid ei tohiks korraga kasutada, kuna nende indeksite kokkupanemisel on agregeeritud mitmete eraldiseivate muutujate mõjud. Lisaks, log-lineaarne regressiooni mudel ei suuda PISA muutujate varieerumisi kõige paremal moel ära selgitada. Mõnede kategooriliste muutujate efekt on kategooria lõikes erinev, ehk tegemist on mittelineaarse mõjuga (näiteks, efekt alguses suureneb ja pärast kahaneb). Lõpuks, õigete muutujate valimine, mudelisse kaasamine ja efektide interpreteerimine on ambitsioonikas ülesanne. Näiteks, raamatute muutuja on kognitiivsete oskuste uurijate seas väga populaarne, aga kas tõesti just raamatute arv mõjutab õpilase PISA tulemusi? Mida rohkem raamatuid sul kodus on, seda parem on su PISA tulemus? Seega ei tohi lineaarsete regressioonimudelite puhul ajada segi korrelatsiooni ja kausaalsust ning raamatuid ja nende positiivsete efekti peaks tõlgendama kui pereefekti – raamatud näitavad seda nähtamatut midagi, mis transformeerib pere kõrgema kultuuritausta PISA test tulemusteks.