Estimating the education production function for cognitive and non-cognitive development of children in Vietnam through structural equation modelling using Young Lives data base

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September 2017

Paper submitted in part fulfilment of the requirements for the degree of Master of Science in Quantitative Research Methods at University College London.

The data used come from Young Lives, a longitudinal study of childhood poverty that is tracking the lives of 12,000 children in Ethiopia, India (Andhra Pradesh), Peru and Vietnam over a 15-year period. **www.younglives.org.uk**

Young Lives is core-funded from 2001 to 2017 by UK aid from the Department for International Development (DFID) and co-funded by the Netherlands Ministry of Foreign Affairs from 2010 to 2014. Sub-studies are funded by the Bernard van Leer Foundation and the Oak Foundation.

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Report for MSc in Quantitative Research Methods
Institute of Education, University College London

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September 2017

Word count: 10,774

Acknowledgements

I am grateful to my supervisor, Dr. Ozan Aksoy, for his continuous guidance and advice that enabled me to explore a topic of great interest to me.

Quisiera agradecer, igualmente, a los pilares que considero claves para mi desarrollo intelectual.

Gracias al Gobierno Ecuatoriano por invertir en mi educación superior y permitirme estudiar a tiempo completo.

Gracias a mi madre, Marianita Espinosa, que dedico un gran parte de su vida a formarme como persona para que tenga los principios y valores necesarios para alcanzar cualquier hazaña.

Gracias a mi padre, Eduardo Grijalva, que nunca dejo de priorizar mi educación ofreciéndome siempre las mejores oportunidades de estudio a lo largo de mi vida.

Gracias a mi esposo, Diego Puente, por siempre recordarme lo maravillosa que soy.

"Education is the most powerful weapon which you can use to change the world."

Contents

Abstract

This paper attempts to shed light on the education process of cognitive and non-cognitive skills by using cross-sectional empirical data from Vietnam. Given the evidence of the benefits that education brings to individuals and society; a better understanding of the education process of multiple educational outcomes is essential. The main purpose of this study is to incorporate the analysis of non-cognitive skills, as a relevant educational outcome, in order to simultaneously estimate the production of educational outcomes (i.e. cognitive and non-cognitive skills) as a more realistic formulation of the education process. The education production function is used as the conceptual framework to empirically model the education process since it is a powerful tool to understand the combination of school inputs that influence educational outcomes. The estimation approach used to simultaneously estimate the production of both outcomes is simultaneous equation modeling. In order to estimate the parameters, maximum likelihood method is used. The information from Young Lives database is sourced as it contains key information about the learning environment of the child. The educational inputs included in the estimation are child, school, teachers and family characteristics. The results obtained from the estimation imply that child's characteristics influence cognitive and non-cognitive development. In this line, the variable with the greatest effect on both educational outcomes is the child's relation with their peers. This is an interesting finding since a non-tangible input has a relevant effect on a child's academic performance and personal development. In terms of academic achievement, a family's socio-economic status is only found to have a strongly determinative effect on a child's cognitive skills. Non-cognitive skills are found to be more likely to be determined by a child's relation with their parents.

Key words: cognitive skills, non-cognitive skills, education production function, structural equation modeling

List of figures

List of tables

Abbreviations

EPF: Education production function

GNI: Gross national income

HTC: Human capital theory

MAR: Missing at random

ML: Maximum likelihood

MLMV: Maximum likelihood with missing values

PISA: Programme for International Student Assessment

SD: Standard deviations

SEM: Structural equation modeling

SEF: Self-efficacy

SES: Self-esteem

SR: Structural regression model

1. Introduction

This paper explores the education process behind the development of cognitive and non-cognitive skills of primary school children in Vietnam. A large body of literature discusses the benefits accrued in life based on education (Psacharopoulos & Patrinos, 2002), and the strong association between national investment in education and economic growth (Hanushek & Kimko, 2000). Given the multiple benefits of education, in the 1960s policy makers paid attention and reflected upon the relation between the allocation of educational inputs and the multiple outcomes (Mighir & Rivkin, 2011). In this context, the production function approach was developed to think about which resources make a difference for student outcomes (Brewer & Hentschke, 2010). There is a vast body of research on the education production function for academic achievement (Tood & Wolpin, 2003). However, this approach is mostly limited to the study of cognitive development. Although schooling plays a pivotal role in the socialization of individuals, preparing them to 'function' in a modern society as 'competent adults', the analysis of which educational inputs contribute to non-cognitive development is scarce (García, 2013).

This paper, therefore, seeks to fill this gap in the literature by exploring which factors of the education production function influence educational outcomes. In this sense, this study fosters the consideration of multiple educational outcomes as the main output of the education process going beyond the analysis of academic achievement. Firstly, the study attempts to make a theoretical contribution by arguing that cognitive and non-cognitive skills are equally important outcomes, and the production process behind them should be analysed together. Secondly, there is a methodological contribution: the study implements a non-traditional approach to estimate simultaneously the two production functions leading to cognitive and non-cognitive skills.

In particular, the study addresses the following research questions: (i) are there educational inputs influencing cognitive and non-cognitive skills simultaneously, (ii) which educational inputs matter for cognitive achievement the most, and (iii) which educational inputs influence non-cognitive development the most? The first question involves the simultaneous estimation of the production of cognitive and non-cognitive skills in order to explore which educational inputs are associated with these educational outcomes. The other two questions entail the analysis of which educational inputs influence only cognitive skills, and which influence only non-cognitive skills.

To answer these questions, the production of cognitive skills is measured as educational achievement in mathematics and Vietnamese reading comprehension. On the other hand, non-cognitive skills are measured by personality traits, such as self-esteem and self-efficacy which are reported by the student. To account for simultaneity, between the outcomes and the educational inputs, a structural equation model is used. The recurrent limitations of this kind of analysis are empirical since children's longitudinal data is scarce, and since certain key educational inputs are omitted because they cannot be accurately measured (Smith, 1999). Nevertheless, the conceptual analysis of the education production function is well suited for policy-oriented research in education (Monk, 1989).

It is worth to point out that this research has a threefold contribution. It aims to account for (i) non-cognitive skills as a relevant educational outcome, (ii) to estimate the production of educational outcomes simultaneously as a more realistic formulation of the education process, and (iii) to propose an education production function for non-cognitive skills.

Given that the study focuses on Vietnam, a brief discussion of the educational context in this country is needed. First, to better contextualise the education process it is necessary to briefly explain the historical reforms of the Vietnamese education system. Until 1980, the Soviet model was implemented, establishing the commencement of free public education (Hang, 2015). In 1986, *Doi Moi* economic reforms led the country to a market economy which gradually modified the education system by including co-payments to supplement state budget (Duc & Hang, 2016). In the early 1990s, Vietnam's primary education budget was constrained by the Word Bank's financial reforms. At the same time, policies to improve education quality were undertaken (Mehotra & DelaMonica, 1998). In 1997, several decrees were issued to decentralise the structure of the education system, and to increase civic participation and community responsibility in order to contribute to the education system (Resolution 90).

In addition to this particular features of the education system, it is recognised worldwide that Vietnam has a high academic achievement. The 2015 PISA (Programme for International Student Assessment) results placed Vietnamese pupils 22nd across 72 countries in tests of reading, mathematics, and science (OECD, 2015). Vietnam is an education outlier since it is the only low-income country that performs at the same level as high-income countries, having similar academic results as New Zealand and Sweden. The academic performance is striking considering that Vietnam gross national income (GNI) per capita is $6,000 in 2015, and the annual GNI per capita growth averaged 4.15% (World Bank, 2017).

The study is organised as follows. Chapter 2 presents a critical review of the literature on the concept of education production function. Chapter 3 sets out the methodology concerning the modeling procedure, model specifications, and properties of the estimation approach. Chapter 4 describes the database and reports descriptive statistics for dependent and independent variables. Chapter 5 includes interpretation and discussion of the results for cognitive and non-cognitive skills as outcome variables. Finally, Chapter 6 concludes with a summary of results and policy recommendations.

2. Literature Review and Conceptual Framework

2.1 Education production function: a theoretical framework to understand the education process

The origins of the education production function

This research is embedded within the field of economics of education. The first line of research within the economics of education is to study whether there is an association between schooling and individuals' outcomes in the labour market (Brewer and Hentschke, 2010). The theoretical framework used to approach this enquiry is human capital theory (HCT) mainly developed through the work of Schultz (1963), Becker (1964), and Mincer (1958, 1970). This theory focused on the idea that education increments individuals' productivity capacity through the accumulation of skills and knowledge which in later stages of life is transformed into higher earnings.

This premise led economists to get interested in the education process behind the accumulation of skills and knowledge envisaged by the HCT. Vandenberghe (2010) argues that HCT is solely concerned with the individual's demand for education, and the decision of investment. Complementary to the HCT, the production function approach aims to understand the supply side to shed light on the education process.

In this line, economists have sought to understand how education is produced in two different ways (Brewer and Hentschke, 2010). One way is to treat education as a production function where schooling and other inputs are processed and produce outputs. This approach would be used as the analytical framework of this study, and it is explained in detail further down. Another way is to examine the education process as a system, where different agents seek to coordinate others in the performance of work. This analysis would fall into the area of principal-agent theory which seeks to capture the complexity of delegating decisions rights between school principals and their subordinates (i.e. teachers).

The concept of the education production function and its implications

The concept of the education production function (EPF) is based on the idea that there is an education process, in other words, that there is something systematic about the transformation of schooling inputs into learning outcomes (Monk, 1989).

The use of the term 'production function' has a specific connotation in the interpretation of results (Hanushek, 1979). The technical meaning of a production function is that it describes the technical relation between inputs and outcomes, expressing the maximum level of outcome for each possible combination of inputs (Krugman, 2009).

In the case of firms, engineers know the technical process of production necessary for a particular item. On the contrary, in education, the production process is not exact, and the technical process defining the maximum 'amount' of educational outcomes obtained by a given combination of inputs has inconsistent results (Bowles, 1970). Even with these considerations in mind, the EPF still is a powerful conceptual tool for policy-oriented research in education (Hanushek, 2007).

2.2 Education production function: conceptual specifications

Cognitive skills as an outcome of education

In the EPF literature, a primary goal of the empirical research is to understand the combination of school inputs that influence cognitive skills (Todd and Wolping, 2003). Gintis (1971) defines cognitive skills as the individual capacities to "*logically combine, analyse, interpret and apply informational symbols*" (p. 268). The analysis of cognitive skills in the EPF is mainly defined by academic achievement leaving other cognitive elements on the side. The reason for this is that social or individual valued features, such as economic performance, are themselves functions of scholastic achievement (Bowles, 1970). It is worth mentioning that economists have paid a lot of attention to the influence of cognitive skills on earnings (Haushek and Woessmann, 2008; Psacharopoulos & Patrinos, 2004), and overall labour market performance (OECD, 2016), social mobility and inequality (Jerrim & Vignoles, 2011; Bowles and Gintis, 2000), and personal health (Johnston et al, 2010).

Academic achievement is usually measured by standardised test scores. However, the use of standardised tests scores raises concerns. Firstly, due to a lack of satisfactory external validation, it is uncertain whether tests cover knowledge or skills valued by society (Hanushek, 1979). Secondly, tests scores are subject to some error since they contain the true value of the measurement plus an error (Bowles, 1970). Nevertheless, there still are strong reasons for the use of test scores as a measurement of academic achievement. The most persuasive argument is that continuation in schooling is based on the performance of students in tests, thus tests scores are indeed related to future success (Hanushek, 1979).

Selection of schooling and other educational inputs

In order to rigorously estimate the EPF, all factors that could possibly influence the learning outcomes have to be identified and included in the analysis. This section highlights the inputs that are most frequently considered.

According to Bowles (1970), there are four key educational environments: (i) home, (ii) community, (iii) peer groups, and (iv) school. Smith (1999) suggests that at home parents play a major role in verbal interaction, variables such as parental education, family structure, and parental expectations are considered aiming to capture the interaction and communication between the child and his/her family. Furthermore, the home environment is also evaluated, in terms of parental attitudes towards schooling, through variables such as reading material available at home, and parent's income. This last variable is commonly measured through 'proxies', such as portable assets or consumer durable goods. In the school environment, Bowles (1970) proposes that there are four important dimensions: (i) teacher quantity, (ii) teacher quality, (iii) school policy, and (iv) school facilities. In this line, inputs related to the school environment include variables, such as educational level of teachers, teachers' attitudes, other measures of teachers' 'quality', school policies, class size, school facilities (e.g. laboratories, libraries) as the main ones (Bowles, 1970). In terms of inputs related to peer influences, studies include information on academic achievement of classmates (Smith, 1999). Finally, the learning environment in the community is measured through socio-economic variables of the social milieu.

There is a lack of consensus over which inputs precisely influence children's performance and to what extent (Parcel & Menaghan, 1994; Hedges et al, 1994). However, Hanushek (2003) and Krueger (2003) note that this lack of consistency is due to the use of different model specifications and different data sources. Nevertheless, previously listed variables have proved to have some effect on learning outcomes.

2.3 An extended education production function approach

Non-cognitive skills as an outcome of education

As aforementioned, the majority of education production function studies focus mainly on cognitive skills as the main outcome of education (Hanushek, 1979). However, just as for cognitive skills, there is a wide research body indicating the relevance of non-cognitive skills for academic achievement (Heckman & Rubinstein, 2001), economic success (Hogan & Roberts, 200; Barrick & Mount, 1991), civic behaviour, health and criminal activity (Almlund et al, 2011). Thus, it is surprising that non-cognitive skills have been overlooked as an outcome of the education process (Carneiro et al, 2007). Given that non-cognitive skills are important in itself (Marsh & Yeung, 1997), and play a main role in determining other desirable individual and social outcomes (Noftle & Robins, 2007). It is relevant to explore which factors are driving the production of these skills, in other words, the education production function of non-cognitive skills. The purpose of having an EPF for non-cognitive skills is to contribute to the understanding of which school and social interventions could influence these skills (Levin, 2012).

It seems relevant to define non-cognitive skills. There are many concepts to explain non-cognitive skills; they can be seen as personality, social and emotional traits (Kniesner & Ter Weel, 2008), as well as, attitudes, behaviours and values (Levin, 2012). This broad definition raises the concern of whether non-cognitive skills are personality traits or skills. This enquiry is relevant to be briefly addressed since personality traits have been commonly understood as fixed traits developed at an early age in the child's life (Heineck and Anger, 2010), whilst the notion of skills is that they are malleable (Gutman & Schoon, 2013). In this particular case, it is expected that they are acquired through education and shaped by the education process. Cunha et al (2010) present theoretical (Cunha & Heckman 2007; Cunha et al, 2006) and empirical evidence (Brunello & Schlotter, 2011; Cunha & Heckman; 2008) of the evolution of children's non-cognitive skills at different stages of their life cycle. The results are consistent and imply that non-cognitive skills are malleable throughout the children's life cycle and are influenced by parental investments. Furthermore, Almlund et al (2011) argue that non-cognitive traits are responsive not only to parental behaviour, but also to investments in education. Thus, it is concluded that non-cognitive skills are malleable by the education process, and that within the scope of this study non-cognitive skills and non-cognitive traits are referred to as very similar constructs.

Specifications of the education production function for non-cognitive skills

The first stage of defining the EPF for non-cognitive skills is to identify which particular skills should be worth to analyse and why. There is no established rule on how to select non-cognitive traits for the analysis (Heckman and Rubinstein, 2001). Note that this research will be centred in examining self-esteem and self-efficacy. These non-cognitive skills are selected for the following reasons. First, it is common to find information in most educational datasets about personality related outcomes, such as self-esteem and self-efficacy. Second, previous analyses in the same area have used these traits and found significant results (Levin, 2012; Duckworth & Seligman, 2005; Wagerman & Funder, 2007). Finally, these traits are theoretically important. Self-esteem is related to self-worth (Jordan et al, 2015), and self-efficacy is linked to one’s capability to organise and implement strategies to effectively accomplish tasks (Schunk, 1984; Bandura, 1982). Not only identifying which non-cognitive traits is challenging, but measuring them is also a complex endeavour. A standard strategy to provide metrics of non-cognitive traits is the use of self-reported surveys through which information is synthesised ex-post with factor analysis techniques[1] (OECD, 2016).

A second stage is to ascertain which inputs can influence these non-cognitive outcomes. Empirical evidence examining the education process behind non-cognitive skills is scarce. Boardman et al (1973, 1977) are one of the first scholars to emphasise that education should be considered as a process with multiple outcomes. Boardman et al (1977) model and estimate a simultaneous equation model considering cognitive and non-cognitive skills as learning outcomes. Besides, examining the relation between inputs and non-cognitive outcomes, the research delves into the association between outcomes, establishing whether self-esteem influences achievement or vice-versa. In this study, it is proposed to define the EPF of non-cognitive skills similarly to the EPF of cognitive skills by including variables to control for home background, school and teacher features, and child characteristics. A

[1] Factor analysis techniques is sensible to identify non-cognitive skills by capturing the underlying or latent factors distribution (Harman, 1976).

more recent work done by García (2013), estimating simultaneously educational outcomes, defines the EPF of non-cognitive skills by including variables related to child, family and school characteristics as well. Based on these previous studies, it seems appropriate to include the same set of variables to predict both cognitive and non-cognitive skills. Using the same set of predictor variables also helps to determine whether the same factors influence both cognitive and non-cognitive skills in the same way, and if not, which variables influence which outcomes.

3. Methodology

In the previous section, it was discussed why the education production function is an appropriate analytical framework to understand the education process behind multiple educational outcomes. In this section, the empirical model of the education production function is presented along with the estimation approach.

3.1 Estimation model

Education production function equation

The production function of education does not have one unique way to be depicted. There are small variations on notations among authors (Glewwe & Kremer, 2006; Tood Wolpin, 2003; Hanushek, 1979), however, the EPF model is generally conceptualised as follows:

$$A_{igt} = f_a\left(Q_{ig}^{(t)}, C_{ig}^{(t)}, H_{ig}^{(t)}\right), \tag{1}$$

where A is vector of skills learned, in this case cognitive and non-cognitive, at time t for the ith student in school g; Q is a vector of school and teacher characteristics cumulative to time t; C is a vector of child characteristics (including 'innate ability') cumulative to time t; H is a vector of family inputs (e.g. reading stories to the child) and household characteristics cumulative to time t (Glewwe & Kremer, 2006).

The functional form of the equation is given by f_a which in general is specified as a linear and additive combination of educational inputs (Todd Wolpin, 2006).

$$A_{igt} = \beta_0 + \sum_{p=1}^{P} \beta_p * Q_{ig,p}^{(t)} + \sum_{l=1}^{L} \beta_l * C_{ig,l}^{(t)} + \sum_{j=1}^{J} \beta_j * H_{ig,j}^{(t)} + \varepsilon_{ig}^{(t)}, \tag{2}$$

where A_i represents cognitive or non-cognitive skills learned by student ith in school g; Q is a vector of p different variables of school characteristics cumulative to time t; C is a vector of l different variables of child characteristics cumulative to time t; H is a vector of j different variables of family characteristics cumulative to time t; and ε_i is an stochastic error term containing other unobservable factors cumulative to time t (García, 2013).

Education production function limitations

The production of education as shown in equation (1) is a cumulative and iterative process, meaning that the educational outcome of each student at each point in time is *per se* a function of prior schooling and educational inputs (Todd & Wolpin, 2006). Given that the education production is portrayed as cumulative a first limitation appears. Inputs have some lasting effect on current outcomes, nevertheless the path of adjustment, in other words, the diminishing effect of each past input in explaining a present output, is unknown (Hanushek, 1979). Even if the 'adjustment rate' of past inputs is modelled, there still is a data constraint to meet with all the requirements of information. One way to circumvent this data limitation is through a 'value-added' model which measures inputs from over two periods (Todd & Wolpin, 2006). However, most of EPF analyses use cross section measure, due to data availability.

The next major empirical problem is the considerable measurement error of variables which occurs in different forms. A first issue is to measure 'innate ability' of the child since the omission of this important variable biases other estimated coefficients (Todd & Wolpin, 2003), but a consensus has not yet been achieved on how to capture its effect and whether the bias is positive or negative (Lang, 1993). A second problem is that family characteristics are not directly measured since they are proxied by other observable attributes, nevertheless, these measurements do capture historical factors (e.g. socio-economic status) (Hanushek, 1979). The last issue is related to the absence of a conceptual framework that includes the measurement of school process characteristics (e.g. class organisation) (Hanushek, 1979; Berman & McLaughlin, 1975). Nevertheless, school inputs, in general, are measured correctly.

Lastly, the EPF functional form as shown in equation (2) has certain implications to be considered. The EPF is modelled as a linear function, meaning that there is independence of the various inputs, and that variables coefficients are conditioned to have a constant marginal effect. Although other functional forms, such as logarithmic models, have been reviewed (Gyimah-Brempong, & Gyapong 1991; Smith, 1972; Coleman, 1966), scholars have broadly used a linear additive form (Levin, 1980; Hanushek, 1972). It is worth mentioning that a linear functional form has certain drawbacks. First, it assumes that different educational inputs have separate effects rather than a joint one. Second, it assumes that educational inputs can be combined in the best way to reach the production frontier where resources are optimally and effectively allocated (Levin, 1980). Nevertheless, Hanushek (1972) has proved that a linear functional form for the EPF has rigorous and reliable results.

3.2 Estimation approach

Structural Equation Modeling

Recall that this study aims at the simultaneous analysis of the production of cognitive and non-cognitive skills since it represents more accurately the education process. In this sense, structural equation modeling (SEM) is used given that it is able to estimate a set of linear simultaneous equations.

- Model properties

There are three main characteristics of this method which are statistically appropriate for this analysis. First, this model can include concepts that are theoretical, but that can be measured through their 'manifestation' on several indicators (i.e. latent variables) (Raykov & Marcoulides, 2011). For this study, this property allows the measurement of self-esteem and self-efficacy which have been selected as two main traits of non-cognitive skills. Second, SEM accounts for potential measurement error, in variables that are thought to measure the underlying latent variable, through an error term per indicator variable. It also estimates variance of errors, as well as, the latent variable as parameters (Boomsma et al, 2012). This characteristic of the model is essential yielding more precise estimates than conventional regressions, given that the conventional EPF estimation is known to have major problems related to measurement error as previously mentioned. Moreover, this property enables to test hypotheses regarding the potential relation between the error terms and other parameters (Kaplan, 2000). Finally, SEM fits matrices of interrelation between all outcome variables simultaneously (Kline, 2011). This enables to have an analysis of multiple associations between inputs which mimics better the educational context.

- Model assumptions

There are a number of assumptions of structural equation models that have to be satisfied to ensure accurate inference. The assumptions underlying the model are (i) multivariate normality, (ii) random missing data, (iii) correct model specification, (iv) exogeneity of explanatory variables (Kaplan, 2012). Under the first assumption - multivariate normality

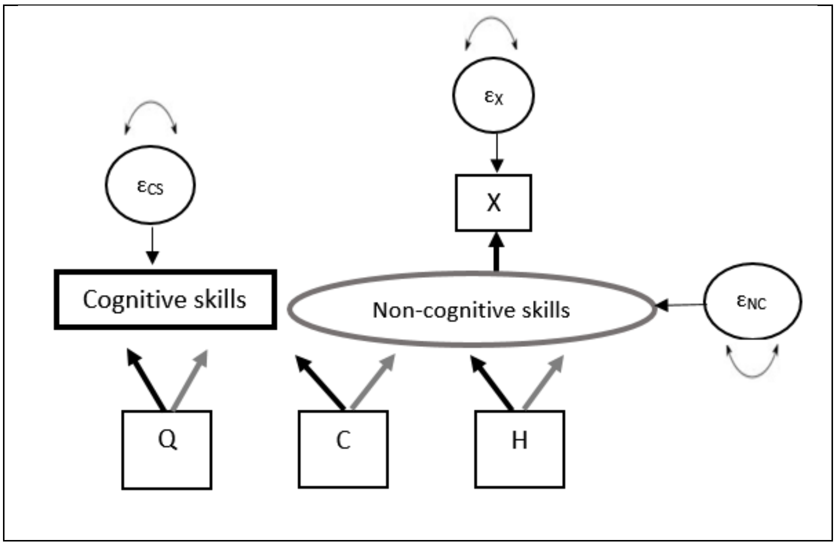
- each observation is assumed to be derived from a population that follows a multivariate normal distribution. This assumption is central to the estimation of SEM parameters through maximum likelihood[2] (ML) since the ML estimator follows a continuous and multivariate normal distribution (Kaplan, 2012). In this research, the estimation of parameters uses ML method, thus multivariate normality is assumed. Under the second assumption - random missing data - units of analysis have missing values in a random fashion, thus the missing data mechanism is ignorable. SEM has several approaches to model missing data under the assumption that incomplete data is missing at random (MAR) (Lee, 2007; Allison, 2003). Note that these SEM approaches that rely on MAR are significant improvements compared with conventional estimation routines which typically implement list-wise deletion (i.e. omitting cases which have at least one missing value). Under the third assumption - correct model specification – it is assumed that the fitted statistical model represents the actual data generating process. Finally, under the fourth assumption - exogeneity of explanatory variables- any omitted input is assumed to be orthogonal to the included ones (Kaplan, 2012). In addition to these assumptions, SEM has further identification requirements, such as order condition and rank condition (for an explanation of these see Appendix 1).

Structural Equation Modeling for the production of educational outcomes

A starting point to use SEM is to correctly define the model (Hoyle, 2012). As an initial stage of model specification, it is useful to represent the set of structural equations in the form of a path diagram. Figure 1 illustrates a simplified version of the path diagram of SEM where cognitive and non-cognitive skills are simultaneously estimated.

[2] The explanation of maximum likelihood estimation is beyond the scope of this research, however for more details see Wooldridge (2013) and Verbeek (2012).

Figure 1. Path diagram of the Education Production Function for cognitive and non-cognitive skills



- Path diagram

In path diagrams, observable variables are represented with a square or a rectangle, and unobservable variables, also known as latent variables, are symbolised with a circle or an ellipse (Raykov & Marcoulides, 2006). This figure indicates that cognitive skills are observable, along with educational inputs given by school (Q), child (C) and family (H) characteristics. It is argued that cognitive skills are observable since they are measured by standardised scores in mathematics and Vietnamese reading comprehension. On the other hand, non-cognitive skills and error variance[3] (ε) are defined as latent variables since they are not directly observed. It is claimed that non-cognitive skills, which in this research are measured by self-esteem and self-efficacy, are indirectly observed since children's answers to a personality questionnaire are used as indicators (X) of measurement. Thus, this is a partially latent structural regression model[4] since cognitive skills are considered and assumed to be observable, whilst non-cognitive skills are estimated as a latent variable.

Also, in this figure, a single arrowhead shows a directional effect of one variable on another, whilst two arrowheads indicate a correlation or a covariance among variables (Kline, 2011). Based on the model specifications of the EPF, it is assumed that educational inputs have a

[3] Error variance is considered a latent variable since it cannot be observed on raw data (Kline, 2011).

[4] A structural regression (SR) model is the synthesis of a structural model and a measurement model. SR is a structural model because it represents hypotheses among the variables, and it is a measurement model since it represents hypotheses about relations between indicators and factors for latent variables (Kline, 2011).

direct effect on educational outcomes, thus, these variables are connected by a single arrowhead. The two arrowheads re-entering the error variance of cognitive skills is capturing whether there is an association between mathematics and reading errors. Similarly, the two arrowheads re-entering the error variance of non-cognitive skills is measuring the correlation between self-esteem and self-efficacy errors.

- System of equations

A second stage of model specification is to denote the set of structural equations. The general equation of structural equation model is presented in Appendix 2, and the specific notation of the estimated system of equations is as follows.

$$A^{m}_{ig\_2013} = \beta_0 + \sum_{p=1}^{P} \beta_p * Q^{(2011)}_{ig,p} + \sum_{l=1}^{L} \beta_l * C^{(2011)}_{ig,l} + \sum_{j=1}^{J} \beta_j * H^{(2011)}_{ig,j} + \varepsilon^{(2011)}_{ig}, \qquad (3)$$

$$A^{r}_{ig\_2013} = \beta_0 + \sum_{p=1}^{P} \beta_p * Q^{(2011)}_{ig,p} + \sum_{l=1}^{L} \beta_l * C^{(2011)}_{ig,l} + \sum_{j=1}^{J} \beta_j * H^{(2011)}_{ig,j} + \varepsilon^{(2010)}_{ig}, \qquad (4)$$

$$A^{ses}_{ig\_2013} = \beta_0 + \sum_{p=1}^{P} \beta_p * Q^{(2011)}_{ig,p} + \sum_{l=1}^{L} \beta_l * C^{(2011)}_{ig,l} + \sum_{j=1}^{J} \beta_j * H^{(2011)}_{ig,j} + \varepsilon^{(2011)}_{ig}, \qquad (5)$$

$$A^{sef}_{ig\_2013} = \beta_0 + \sum_{p=1}^{P} \beta_p * Q^{(2011)}_{ig,p} + \sum_{l=1}^{L} \beta_l * C^{(2011)}_{ig,l} + \sum_{j=1}^{J} \beta_j * H^{(2011)}_{ig,j} + \varepsilon^{(2011)}_{ig}, \qquad (6)$$

Equations (3) to (6) present the regression of the education production function for mathematics (m), Vietnamese reading comprehension (r), self-esteem (ses), and self-efficacy (sef) respectively. Due to data availability, each regression includes two different time periods. Educational inputs are measured for the scholar year 2011-2012 when Vietnamese children are around 10-11 years old, and educational outcomes are measured in 2013 when the children are 12 years old. This study is a cross-sectional analysis including two different time periods (2011-2012 and 2013), under this specification each structural equation considers as units of analysis the observation for the children at a particular point in time. This model specification of the EPF is categorised by Todd & Wolpin (2006, 2003) as contemporaneous since it is assuming that only contemporaneous inputs matter (in this case inputs from 2011-2012) given that they capture inputs history over time.

- Research hypotheses

Lastly, this approach enables testing the hypotheses of the research questions which are:

H$_1$: There are educational inputs that influence cognitive and non-cognitive skills.

H_2: There are educational inputs that influence cognitive skills.

H_3: There are educational inputs that influence non-cognitive skills.

This model jointly examines which inputs are associated with the aforementioned educational outcomes simultaneously, answering the first hypothesis. Also, this model enables to analyse which educational inputs influence which outcome the most, corresponding to the second and third hypotheses.

4. Data

In the previous section, the model specifications of the EPF is given, along with the estimation method. In this section, the data used to estimate the EPF through SEM is presented.

4.1 Database description

Data source and sampling strategy

The data for this study is from the Young Lives Project which is an international longitudinal study tracking the lives of children over the course of 15 years in four countries: Ethiopia, India (Andhra Pradesh district), Peru and Vietnam. This study follows in each country two cohorts of children. The younger cohort consists of 2,000 children born between January 2001 and May 2002, and the older cohort consists of 1,000 children born between 1994 and 1995 (Huong, 2014). For this purpose, only information from the younger cohort in Vietnam is used.

The Young Lives study sample in Vietnam consists of 20 sentinel sites[5]. The sites were selected in 2001 using a semi-purposive sampling strategy to reflect the diverse socio-economic conditions of children within Vietnam rather than aiming to be nationally representative (Huong, 2014, Barnett et al, 2012). The sampling strategy intends to show changes over time of children's circumstances and the impact on later life outcomes (Nguyen, 2008). A sentinel site was defined as commune-based, and the process of selection of 31 communes is characterised to ensure over-sampling of poor communities and under-representation of the urban sector (Huong, 2014; Tran et al, 2003). The sampling process also considered geographical diversity since it has important differences on socio-economic development (Duc & Hang, 2016). To know the specific location of these sites, see the map shown in Appendix 3.

[5] The concept of sentinel come from health surveillance studies where the site (i.e. cluster in sampling language) represents a certain type of population and the trends affecting those particular people (Huong, 2014).

Contents of the database

Young Lives has two main surveys, for this study both were used and the description is as follows.

- Household survey

Young Lives Project has collected extensive data about the family and the child from four rounds of surveys carried out in 2002, 2006, 2009 and 2013 for both cohorts. When the first round was carried out in 2002 the children of the younger cohort were aged around 1 year (Rolleston & James, 2015). This research uses only the information from the fourth round held in 2013 when the children were aged approximately 12 years since it is the only round that contains non-cognitive skills measurements. During each round, a large household survey is realised, where all children and their caregiver are surveyed and interviewed. Information from community representatives is also collected. This research uses data from the household questionnaire which includes information on parental background, socio-economic status, and child health, as well as information from the child questionnaire which includes time-use, social networks, feelings, attitudes, and reading and mathematics scores (Azubuike & Briones, 2016).

- School survey

In addition, Young Lives has conducted a school survey in 2011-2012. The survey was designed to take place in two waves, at the beginning and at the end of the school year, to trace the academic progress of children during the same year (Young Lives, 2017). This research uses the information on the school survey, but only from the first wave due to data availability. This survey has questionnaires for principals, teachers, and pupils. It also contains information on school facilities, as well as children's tests scores in mathematics and Vietnamese reading comprehension, along with teacher tests in pedagogical content (Rolleston et al, 2013). This survey was conducted over a sub-sample of children from the younger cohort aged between 10 and 11 years in grade 5 (1,138 children), and over a sample of their peers (2,146 children) given a total of 3,284 pupils (Hang, 2015). Data was collected from 176 classes in 56 public schools (Huong, 2013).

4.2 Descriptive Statistic

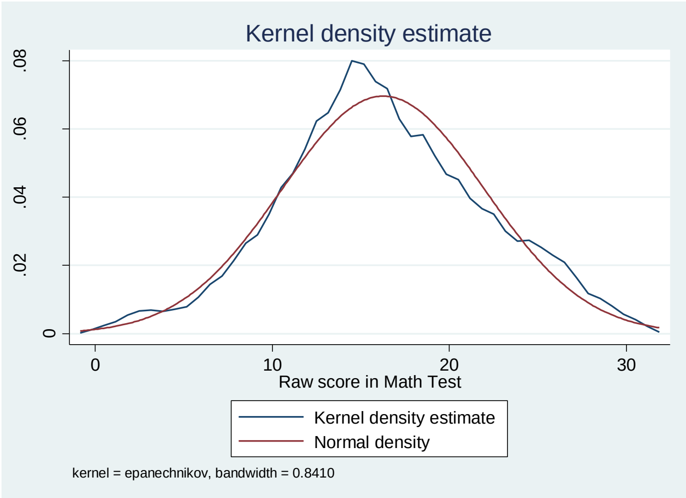
<u>Educational outcomes as dependent variables</u>

Recall that children's cognitive and non-cognitive skills data comes from the household survey in Round 4 in 2013.

- Cognitive skills

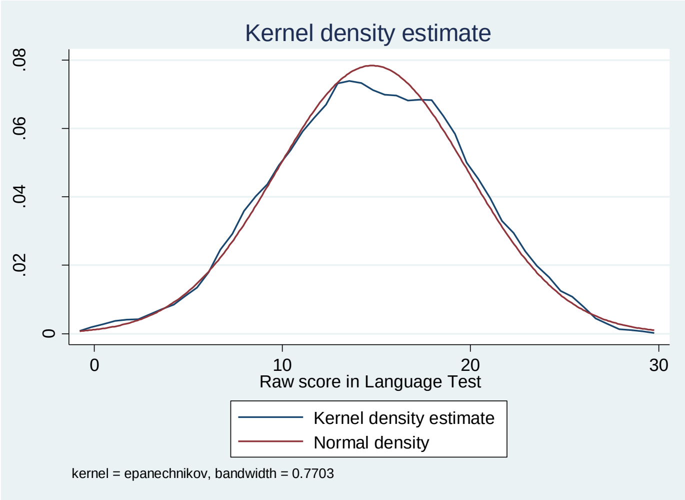
In Round 4, mathematics test consisted of 34 items assessing basic mathematic operation and mathematics problems. The reading test contained 30 questions about the content of three texts (Duc & Hang, 2016).

Figure 2. Kernel distribution of mathematics scores



From Figure 2, it is inferred that the distribution of mathematics scores is close to normal. On average students have 16 points over a total of 34, with 0 as the lowest score and 31 as the highest.

Figure 3. Kernel distribution of Vietnamese reading comprehension



Similarly, Figure 3 indicates that the distribution of reading scores is close to normal. On average students get 14 responses right out of 30, scoring at the lowest 0 and 29 as a maximum. A detail statistical description of cognitive skills is presented in Appendix 4. Also, it is worth to point out that the scale of mathematics and reading scores is changed to z-scores to be included in the model.

- Non-cognitive skills

In the case of non-cognitive skills self-esteem (SES) and self-efficacy (SEF) are chosen. To measure these dimensions which are related to self-worth and a child's sense of agency respectively, a Liker-type personality questionnaire is used. The questions include measures of friendliness, pride, determination, social trust, and networking (Borga, 2015). The answers are based on whether the student 'agrees' or 'disagrees' with a certain statement, ranging responses from strong agreement to strong disagreement (Azubuike & Briones, 2016).

The number of items in the questionnaire that are related to self-esteem and self-efficacy are eight and ten respectively. To measure SES and SEF certain items were selected based on results from an initial factor analysis[6] and the analysis of Cronbach's alpha[7]. The items that do not load highly on the factors were discarded. From eight items related to self-

[6] Factor analysis reports correlated variables in terms of a potentially lower number of 'unobserved' variables called factors (Harman, 1976).

[7] Cronbach's alpha measures how closely related a set of items are as a group (Upton & Cook, 2014).

esteem in the questionnaire, four were selected, and similarly, from ten items related to self-efficacy, four were selected (see Appendix 5). The reduction of the number of items per latent variable to four not only improved the measurement of these latent variables, but also made estimation easier to converge[8]. Furthermore, the distribution of students' responses to the items associated with self-esteem and self-efficacy are shown in Appendix 6.

Educational inputs as explanatory variables

This following section shows the descriptive statistics for the selected variables included in the model. Recall that this information was collected by the school survey in 2011-2012 from public schools only.

- Child Characteristics

Table 1 presents general characteristics, such as age and sex. It also displays variables related to the child's health conditions, such as child's height for age, and how often the child has headaches. It also displays other characteristics that are key determinants of child's cognitive and non-cognitive skills, such as innate ability and motivation. Finally, variables traditionally not included in the EPF are considered. For instance, child's social relation with his/her parents and peers, and feelings and attitudes. These 'non-traditional' variables are relevant inputs, especially for the estimation of non-cognitive skills.

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[8] Note that a SEM which included all 18 items failed to converge after two days of iterations.

Table 1. Descriptive statistics for selected variables capturing child characteristics

Variable	Type	Mean	N	Min	Max
General Characteristics					
Age (months)	Continuous	146.37	1,901	135	163
Sex	Discrete	0.49	1,129	0	1
Health Characteristics					
Child's height for age (standardised score)	Continuous	-1.05	1,900	-6	3.24
Child has headaches frequently	Categorical	0.75	1,127	0	2
Innate Ability					
Child 's academic performance	Categorical	2.43	1,138	0	3
Child 's motivation	Categorical	2.58	1,138	0	4
Social relations					
Child 's relation with parents (index)	Continuous	3.25	1,899	1	4
Child 's relation with peer (index)	Continuous	2.75	1,923	1.12	4
Feelings and attitudes					
Child 's proudness of clothes worn	Categorical	3.40	1,923	1	5
Child 's proudness of work done	Categorical	3.60	1,605	1	5
Child 's perseverance to change life	Categorical	3.96	1,922	1	5
Child makes plans for the future	Categorical	4.04	1,922	1	5
Child works hard to be rewarded	Categorical	4.3	1,870	1	5

- School and Teachers Characteristics

Table 2 demonstrates school characteristics such as infrastructure index and child’s commute time. It is worth noting that Young Lives database has paucity information on schools which influence the number of variables included in the model. However, the database is rich in information regarding teacher’s characteristics. In this sense, there are variables related to pedagogy, measuring how often teachers review and comment homework, and to teacher’s attitudes toward their role and capacities. Table 2 also displays the education level and experience of the principal and the teachers.

Table 2. Descriptive statistics for selected variables capturing school and teacher's characteristics

Variable	Type	Mean	N	Min	Max
School characteristics					
School infrastructure index	Continuous	0.49	1,120	0	1
Pupil's time to get to school (minutes)	Continuous	12.17	1,128	1	60
Teacher's pedagogy					
Teacher's treatment to students	Categorical	1.88	1,128	1	3
Teacher reviews math HW frequently	Categorical	2.39	1,126	0	4
Teacher comments on math HW frequently	Categorical	1.75	1,132	0	3
Teacher reviews Vietnamese homework	Categorical	1.87	1,132	0	4
Teacher comments on reading HW frequently	Categorical	1.62	1,134	0	3
Principal's characteristics					
Principal's years of working experience	Continuous	10.14	1,138	0	29
Principal's education level	Categorical	4.67	1,138	1	5
Teacher's characteristics					
Teacher works in his/her province of origin	Discrete	0.73	1,138	0	1
Teacher's years of working experience	Continuous	16.66	1,110	0	36
Teacher's education level	Categorical	4.31	1,138	1	5
Teacher's attitudes					
Teacher adjusts to students' learning necessities	Categorical	3.03	1,138	1	4
Teacher beliefs that learning overcomes background features	Categorical	3.01	1,130	1	4

- Family Characteristics

Table 3 shows variables related to socio-economic status of the family and the structure of it in terms of number of family members. Also, there are certain variables measuring family 'human capital' through mother's education and the number of books at home. Finally, variables related to family inputs are included capturing the attitudes of the family towards the child's education.

Table 3. Descriptive statistics for selected variables capturing family characteristics

Variable	Type	Mean	N	Min	Max
Socio-economic status					
Household basic service index	Continuous	0.61	1,931	0	1
Household portable asset index	Continuous	0.6	1,931	0	1
Family structure					
Household size	Continuous	4.54	1,931	1	14
Number children in the household under 16	Continuous	1.01	1,125	0	13
Family human capital					
Mother's education level	Categorical	1.86	1,809	0	4
Number of books in the household	Categorical	1.88	1,128	0	3
Family attitudes toward child's education					
No academic support at home	Categorical	2.18	1,138	1	5
Availability of study space at home	Discrete	0.8	1,124	0	1

To conclude the model includes 13 variables related to child characteristics, 14 associated with school and teacher characteristics and 8 measuring family characteristics, given a total of 35 explanatory variables. From the total of variables, 12 are continuous and the rest are either discrete or categorical. All categorical variables are in fact ordinal with around three to five ordered categories. In order to prevent the loss of degrees of freedom[9] of the model, and come up with a parsimonious model, given the high number of independent variables (Rigdon, 1994), all variables are included in the model as continuous. This, in principle, should not result in large misspecifications as all categorical variables are ordered (Finney & DiStefano, 2006).

4.3 Sample selection

There are 2,000 Vietnamese students included in the household survey but only 1,138 are included in the school survey which constrains the number of observation to 1,138. When the model is estimated over all the independent variables with list-wise deletion (Green, 2002), the number of observations decreases to 775

[9] Degree of freedom are the number of values in a study that have the freedom to vary (Grafen & Hails, 2002). The model has 91 degrees of freedom when all variables are included as continuous. In contrast, the degrees of freedom explodes when all ordered variables are included in the model as several dummy variables.

Recall that in section 3.2 it was mentioned that SEM has several approaches to model missing data. One way is through the full information ML method (Lee, 2007; Arbuckle, 1996) where missing units are modelled under the assumption that data is missing at random. For this research, missing data is modelled through maximum likelihood with missing values (MLMV). The general idea of this method is as follows. Observations that belong to the same missing pattern are treated as independent groups, mean vectors and covariance matrices are formed for each independent group, and then they are analysed together to calculate the sample covariance matrices (Lee, 2007). Thanks to this approach the final number of observations in the model remains at 1,943 (with MLMV only observations that are missing in *all* variables are excluded). Scholars have tested that this approach, and concluded that it has a high performance in comparison to other estimation methods with missing data (Enders & Bandalos, 2001).

5. Findings and discussion

This section presents and discusses the results. The association, not causation (Bollen & Pearl, 2012), between educational inputs and outcomes is presented based on the results synthesised in Table 4. Note that similar studies to this one are scarce which makes it more difficult to contextualise and generalise the findings.

5.1 Understanding the relation between child characteristics and educational outcomes

Child main attributes as inputs

Child's general characteristics, such as age and sex, are related differently to educational outcomes. Age has a statically significant relation with cognitive skills but it does not have one with non-cognitive skills. Although the relation is significant with cognitive skills, holding all other variables constant, a child aged one more month improves his/her mathematics score in 0.02 standard deviation (SD), whilst in a similar scenario, the score for reading improves in 0.2 SD.

Child's sex proves to be related to cognitive and non-cognitive skills. Although this variable has a small effect on both outcomes, it is interesting to analyse the sign. For mathematics, girls seem to do worse than boys, but it is the opposite for reading. Another relevant observation is that girls seem to have a lower perception of self-worth in comparison to boys.

Characteristics of child's health are also included as inputs since health is key in determining the development of skills (World Health Organization, 2008), and has a lasting effect throughout a child's life (Figlio et al, 2013).

Child's height for age is considered a good indicator of nutritional status (Attanasio et al, 2015; Field et al, 2009). In this case, it has a significant statistical association but only with cognitive skills, and particularly with mathematics scores. However, the magnitude of the relation is small (SD 0.06).

There is also information on child's 'general' health status which is measured by how frequent the child has headaches. Headaches in children is a common sign of physical illnesses or emotional shocks (Mayo Foundation for Medical Education and Research, 2017). For this case, child's headaches are statistically significant for cognitive and non-cognitive skills. Although the magnitudes of the coefficients for mathematics and self-esteem are small, the coefficient for reading is large. Reading scores decrease by 0.4 SD the more frequent a child has headaches, ceteris paribus.

The innate ability of the child is another key component of the EPF. Although there is a heated debate on how to effectively measure child's innate ability and motivation (Hansen et al, 2004), one way to do it is by reporting teacher's assessment on these dimensions (García, 2013). Young Lives questionnaires ask teachers to gradually evaluate for each child from 'high' to 'low' the child's academic achievement and motivation to succeed at school (Young Lives, 2011).

Table 4 presents that whilst academic performance is strongly linked exclusively with cognitive skills, motivation is related to both skills. Indeed, mathematics and reading scores increase by 0.2 SD and 0.3 SD respectively, the higher the academic performance of the child is. Moreover, both of these scores increment by 0.1 SD for cognitive and non-cognitive skills when the child presents higher motivation levels. Even though motivation is positively associated with non-cognitive skills, the magnitude of the coefficient seems small.

Child socio-emotional aspects as inputs

Child's social relations are included especially to contribute to the estimation of non-cognitive skills. There is a vast literature body discussing how non-cognitive skills are based on the particularities of social interactions (Jordan et al, 2015; Zeigler-Hill, 2012). For this reason, child's relation to their parents and peers are considered as inputs[10]. Table 4 indicates that only for non-cognitive skills the relation that a child has with his/her parents is statistically significant. In contrast, a child's relation with their peers is significant for cognitive and non-cognitive skills.

[10] These variables are measured through an index created from child's responses to several items ranging from strong agreement to strong disagreement see Appendix 7 for further detail.

For non-cognitive skills, it is not surprising that both indices are strongly associated with self-esteem since self-esteem is based on how others value ourselves (Bednar & Petterson, 1995). The effect of 'parents' relation index' on self-esteem is 0.1, whilst the effect of 'peers' relation index' is 0.5. In the case of self-efficacy, relations also play a main role since they determine one's capacity to achieve personal goals in a social environment (Schunk & Zimmerman 2009, Bandura 1994). Self-efficacy has a relatively low association with 'parents' index' 0.08, whilst it has a higher correlation with 'peers' index' 0.4.

In terms of cognitive skills, a positive relation with their peers increases the child's reading score by 0.1 SD, ceteris paribus. Numerous studies have found that child's own achievement and behaviour benefit from exposure to higher-achieving or well-behaved peers, this peer effect has been researched by Duflo et al (2011), Hanushek et al (2003) and especially Sacerdote (2011).

Child's feelings and attitudes are included to further explain non-cognitive skills. Self-esteem and self-efficacy are based on perceptions and judgements on the 'self' (Harter, 2015), thus, child's pride and self-efficacy beliefs should be included in the analysis. Child's feeling of pride and attitudes, such as: changing life situations, making future plans and working hard, have all a statistically significant association with non-cognitive skills, in particular with self-efficacy. However, the magnitudes seem low for all of them.

Also, child's proudness of his/her work has a significant relation with reading scores. Although the magnitude of the coefficient is small (-0.05 SD), it is interesting to point that the sign is negative. This is unexpected since the prouder the child is with his/her work the higher the score should be.

5.2 Analysing the relation between school and teachers characteristics and educational outcomes

<u>School characteristics as inputs</u>

Another pivotal dimension of the EPF is related to **school characteristics**. Table 4 indicates that for non-cognitive and cognitive skills school infrastructure and commuting time to school are statistically insignificant. In the case of school infrastructure, there is no consensus on whether infrastructure has an influence on academic achievement or not (Crampton, 2009). Conversely, there is not much empirical evidence indicating the relation between school infrastructure and non-cognitive skills. However, it could be expected that child's self-esteem is strengthened by going to a school with 'good' infrastructure.

In the case of time spent to get to school, it is expected that additional commuting time has a negative effect on academic achievement (Rivkin, 2010). There is no much previous research on the relation between commuting time and non-cognitive skills, in this sense this research sets a precedent, and apparently there is no association between the two variables.

Teacher's characteristics as inputs

Also, Table 4 shows that **teaching practices** do influence cognitive skills, but they are not associated with non-cognitive skills. These pedagogical practices are measured by teacher's warmth, determined by how 'well' the teacher treats the students, and the type of support that the teacher provides, assessed by the frequency with which reviews and comments on homework are done by the teacher.

For cognitive skills, an improvement of teacher's treatment to the student increases the mathematics score of the child by 0.1 SD, ceteris paribus. Also, there is a statistically significant relation between teacher's revision of mathematics homework and reading and mathematics scores, but the magnitude of the coefficients are small. It is interesting to observe that teaching practices of mathematics teachers influence reading and mathematics scores. It seems that mathematics teachers have an influence on how 'well' students do in other subjects. This could be caused by the fact that Vietnamese education system has a strong component of science in its curriculum (Do, 2009). However, it is unexpected that more feedback given by the teacher on mathematics homework decreases the score of mathematics and reading by 0.1 SD, ceteris paribus. This result is contradictory since teacher's feedback should positively influence academic achievement (Ngware et al, 2014, Hattie, 2009).

Although teaching practices are not associated with non-cognitive skills, it is expected that they affect self-esteem and self-efficacy since the core of teaching is student-teacher interaction which is characterised by an exchange of knowledge and emotions (Brackett & Katulak, 2007; Sutton & Wheatley, 2003).

Principal's characteristics, such as working experience and education level, are not related to cognitive and non-cognitive skills. These variables are usually included in the estimation of the EPF as proxies to assess management and organisational processes of the school (Hanushek, 1979).

Teacher's characteristics are included in the model by measuring the experience, level of education, and province of origin of the teacher. Based on the results of Table 4, teacher's experience and education prove not to be statistically significant predictors of cognitive results. Actually, Krueger (1999) affirms that teacher's characteristics explain relatively little of student achievement. Nevertheless, teacher's education has a statistical relation with non-cognitive skills, but the correlation is low. Hanushek and Rivkin (2010) claim that, although previous literature review affirms that teacher's characteristics have no effects on students' learning, the "*interpretation of research on teachers often confused the effects of specific teacher characteristics with the overall contribution of teachers*" (pg. 267).

Another variable without statistical significance, for cognitive and non-cognitive skills, is whether teachers work in their province of origin. Although there is no consensus on the relevance of this variable as an educational input, there are some previous studies including it as part of the EPF since it is expected that teachers are more engaged when they teach in their community (Hanushek & Rivkin, 2010).

Finally, **teacher's attitudes** towards teaching are included in the EPF. Teacher's attitudes are related to how their behaviour in the classroom can influence students' outcomes (Tschannen-Mora & Hoy, 2007). Teachers who think that they can impact students' learning are more likely to implement didactic innovations, and to use adequate teaching methods to encourage students (Caprara et al, 2006). For cognitive skills, teacher's attitudes are statistically significant, however, it is not the case for non-cognitive skills. Teachers who believe that learning overcomes family background characteristics increase the mathematics and reading scores by 0.2 SD and 0.1 SD, respectively, holding all other variables constant.

5.3 Studying the link between background features and educational outcomes

Family characteristics as inputs

The last component of the EPF is related to family background. A key element characterising family background is its **socio-economic status.** Socio-economic status is measured by using two proxies: access to services and tenure of portable goods. Table 4 demonstrates that these two variables are statistically significant for cognitive skills, for both mathematics and reading, but they are not for non-cognitive skills.

An increase in one point of the service index, holding all other variables constant, increases the score of mathematics and reading by 0.2 SD and 0.3 SD, respectively. Similarly, an increase in one point of the asset index augments the score of mathematics and reading by 0.5 SD in both cases, ceteris paribus. Note that socio-economic status has the biggest influence on cognitive skills in comparison to the other variables included in EPF. This finding is aligned with previous research. Sirin (2005) does a meta-analysis review of more than 300 studies, and concludes that the average effect of socio-economic status on achievement is 0.2-0.5 SD. This effect is explained by Orr (2003) through two mechanisms. Family wealth can be used directly to purchase educational resources or indirectly to expose the child to cultural and social capital. It is unexpected that socio-economic status does not have a relation with self-esteem since various authors argue that it contributes to child's social acceptance (Warner, 1994; Schultz, 1990).

Family structure, measured by the household size and the number of children under 16 years old, has no statistical relation with cognitive and non-cognitive skills. This finding is unexpected since the relation between the number of family members, especially number of siblings, and child's skills development is expected to be significant and negative (Downey, 1995). The 'resource dilution theory' ascertains that parents' resources are limited, and thus, they are diluted among children, affecting children's future performance (Downey, 1995). Another explanation to understand this negative relation is that small families are more oriented towards 'adult values' which favours child's cognitive and non-cognitive skills (Nutall et al, 1976).

Human capital and support from the family as inputs

Family human capital is measured through two proxies: mother's education level and number of books in the household. These variables have a statistically significant association with cognitive skills, but this is not the case for non-cognitive skills. Mother's education is significant for mathematics and reading, both scores increase on average 0.2 SD when mother's education goes one level higher, ceteris paribus. Although the relation between reading scores and number of books in the household is significant, the magnitude of the coefficient is low (0.05 SD). Human capital of the parents is positively related to child's academic achievement since parents with more education behave differently by taking decisions future-oriented and expanding their child's opportunities (Wilson, 2001). It is unexpected that mother's education does not influence self-esteem and self-efficacy since a mother with more education knows and has better means to take better care of her child (Flouri, 2006).

Family endeavour to support the child's education is a relevant dimension to include since it is not related to socio-economic endowment. There are a plethora of ways in which parents can be involved with their child's learning process. In this case, two variables are included: the lack of academic support received at home and the availability of a study space in the house. From these variables, only 'lack of academic support' has a statistically significant relation with cognitive and non-cognitive skills, in particular with reading scores and self-efficacy. The less support the child receives at home affects negatively his/her score, however, the effect is small (SD -0.07). The correlation between 'lack of academic support' and self-efficacy is also negative and low (-0.01). Jones and Rowley (2009) allege that parents' participation is key in child's development since it increases the time of language practice, which influence directly reading scores, and it increases the child's agency scope.

Table 4. Structural Equation Modeling for the production of multiple educational outcomes. Cognitive skills are standardised whereas non-cognitive skills are measured as latent variables with an estimated variance. The item loadings on self-esteem and self-efficacy as well as variance parameter estimates are suppressed for brevity.

	Cognitive skills		**Non-cognitive skills**	
Dependent variables	**Mathematics**	**Reading**	**Self-esteem**	**Self-efficacy**
Child Characteristics				
Age (months)	0.016** (0.005)	0.194*** (0.005)	0.002 (0.001)	0.001 (0.002)
Sex	-0.081** (0.041)	0.108* (0.057)	-0.056** (0.020)	-0.037 (0.026)
Child's height for age (standardised score)	0.063*** (0.019)	0.021 (0.016)	-0.007 (0.005)	0.004 (0.013)
Child has headaches frequently	-0.074** (0.024)	-0.392* (0.023)	-0.024** (0.011)	0.003 (0.014)
Child 's academic performance	0.233*** (0.055)	0.304*** (0.053)	-0.039 (0.026)	0.012 (0.027)
Child 's motivation	0.194*** (0.050)	0.114** (0.057)	0.042* (0.024)	0.048** (0.024)
Child 's relation with parents (index)	0.031 (0.050)	0.086* (0.049)	0.139*** (0.023)	0.085*** (0.024)
Child 's relation with peer (index)	-0.054 (0.047)	0.135** (0.052)	0.544*** (0.030)	0.470*** (0.031)
Child 's proudness of clothes worn	-0.000 (0.036)	-0.015 (0.025)	0.032** (0.013)	0.022** (0.009)
Child 's proudness of work done	-0.046 (0.038)	-0.058** (0.028)	0.012 (0.012)	0.036** (0.015)
Child 's perseverance to change life situation	0.020 (0.023)	0.023 (0.032)	0.015 (0.011)	0.045*** (0.013)
Child makes plans for the future	0.001 (0.020)	-0.021 (0.025)	0.044** (0.014)	0.060*** (0.011)
Child works hard to be rewarded	0.030 (0.028)	0.015 (0.029)	0.009 (0.011)	0.027** (0.011)
School and Teacher Characteristics				
School infrastructure index	-0.227* (0.118)	-0.131 (0.110)	-0.012 (0.045)	0.046 (0.043)
Pupil's time to get to school	-0.002 (0.003)	0.001 (0.003)	0.001 (0.001)	0.000 (0.001)

Teacher's treatment to students	0.157** (0.069)	0.084 (0.070)	-0.034 (0.030)	-0.009 (0.033)
Teacher reviews math HW frequently	0.079** (0.036)	0.068** (0.031)	-0.004 (0.010)	-0.000 (0.015)
Teacher comments on math HW frequently	-0.117** (0.044)	-0.095** (0.045)	0.005 (0.016)	-0.019 (0.020)
Teacher reviews Vietnamese homework	-0.001 (0.034)	-0.038 (0.030)	-0.014 (0.010)	0.015 (0.015)
Teacher comments on Vietnamese HW frequently	0.022 (0.033)	0.039 (0.037)	0.014 (0.015)	0.004 (0.020)
Principal's years of working experience	0.002 (0.007)	-0.005 (0.004)	0.000 (0.002)	0.000 (0.001)
Principal's education level	-0.043 (0.070)	-0.101* (0.059)	0.039 (0.029)	0.001 (0.021)
Teacher works in his/her province of origin	0.081 (0.060)	0.046 (0.068)	0.010 (0.030)	-0.001 (0.021)
Teacher's years of working experience	-0.001 (0.003)	-0.000 (0.003)	-0.002 (0.001)	-0.001 (0.001)
Teacher's education level	-0.006 (0.041)	-0.063* (0.036)	0.031** (0.013)	0.017 (0.018)
Teacher adjust to student's learning necessities	0.037 (0.043)	-0.082* (0.045)	0.002 (0.026)	0.010 (0.029)
Teacher beliefs that learning overcomes background features	0.188** (0.069)	0.087* (0.046)	0.025 (0.021)	-0.007 (0.016)
Family Characteristics				
Household basic service index	0.263** (0.112)	0.367*** (0.092)	0.003 (0.045)	0.001 (0.050)
Household portable asset index	0.548*** (0.221)	0.546*** (0.168)	-0.002 (0.054)	-0.054 (0.054)
Household size	-0.007 (0.015)	-0.008 (0.014)	0.004 (0.005)	-0.002 (0.005)
Number of children in the household under 16	0.023 (0.019)	0.024 (0.018)	0.008 (0.009)	0.005 (0.010)
Mother's education level	0.173*** (0.026)	0.184*** (0.028)	-0.010 (0.011)	-0.008 (0.013)
Number of books in the household	0.040 (0.025)	0.055** (0.026)	-0.002 (0.010)	0.009 (0.010)

No academic support at home	-0.050* 0.027	-0.079** (0.032)	0.005 (0.011)	-0.019** (0.011)
Availability of study space at home	0.126* (0.066)	-0.030 (0.725)	0.012 (0.026)	0.054 (0.032)
Constant	-5.026*** (1.004)	-3.720*** (0.932)		
Observations			1,943	

Note: standard errors are clustered by school level assuming independence across clusters and correlation within clusters among students (Wooldridge, 2013). All the observation with no values for school identification where grouped as belonging to the same school assuming MAR. Statistics of goodness of fit cannot be obtained for SEM when error are clustered. For this reason, Chi-squared, RMSEA, CFI or other statistics of goodness of fit are not reported in Table 4.
Cluster standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

6. Conclusions and policy recommendations

This paper attempts to shed light on the education process of cognitive and non-cognitive skills by using cross-sectional empirical data from Vietnam. The education production function is used, as the conceptual framework to empirically model the education process, since it is a powerful tool to understand the combination of school inputs that influence educational outcomes. This study aims to simultaneously estimate the production of cognitive and non-cognitive skills since it is a more realistic formulation of the education process. This implies that the same educational inputs used to determine the production of cognitive skills are used to explain the production of non-cognitive skills. It is therefore claimed that both outcomes are part of the same education process experienced by the child. The estimation approach used to simultaneously estimate the production of both outcomes is structural equation modelling. In order to estimate the parameters, maximum likelihood method is used. The Young Lives database is sourced as it contains key information about the learning environment of the child, such as school, family and child characteristics. Due to this, the model has relevant information from all the pivotal actors involved in the learning process.

Are there educational inputs influencing cognitive and non-cognitive skills simultaneously?

Recall that this study purpose is to determine the set of predictors which influence both cognitive and non-cognitive skills. The results indicate that most of the variables included as charactertistics of the child influence both learning outcomes: cognitive and non-cognitive skills. The main attributes of the child, such as sex, motivation and ‘general’ health status, are associated with the development of both skills. A child’s socio-emotional aspects, such as pride and the relation with parents and peers, play a significant role in determining the production of educational outcomes as well. It is worth mentioning that the input with the greatest effect on both educational outcomes is the child’s relation with their peers. Family characteristics also have an influence on the education process of both outcomes. However, among the variables related to family features, only academic support received at home is relevant.

Which educational inputs matter for cognitive achievement the most?

It is also important to understand which variables influence cognitive skills. Based on these findings, there is empirical evidence to confirm that a child's cognitive achievement is mainly explained by their family's characteristics. The proxies measuring family socio-economic status have the largest effect on academic achievement. This is followed by the effect of child's 'innate' ability. Lastly, the feedback that is given by the teacher also influences heavily mathematics and reading scores. Regarding cognitive skills, there are statistically significant variables found amongst all the actors which take part in the education process.

Which educational inputs influence non-cognitive development the most?

It is also important to know which variables influence non-cognitive skills. The educational inputs correlated with non-cognitive development are mainly child characteristics, followed by family features. In terms of child characteristics, the variable related to child's relation with their peers has the biggest correlation with both their self-esteem and their self-efficacy. Morevoer, child's relation with their parents has the second biggest correlation. As for the family characteristics, family support for a child's academic life is correlated with the child's development of non-cognitive traits.

For policy makers, these results have several implications. Usually, educational analysts focus on making decisions at the school level where they can deliberately influence outcomes. From the previously mentioned results, cognitive and non-cognitive skills are apparently not influenced simultaneously by school and teacher features. In this sense, the policy makers' field of action might be seen as constrained. However, another way to understand these results is to broaden the scope of long-term school planning and include new elements that have traditionally not been considered. For instance, resources should be allocated (i) to strengthen health programmes at school, (ii) to promote the sense of belonging and pride of children through coursework, and (iii) to train teachers so that they are 'capable' to generate a 'positive' learning atmosphere where children can easily create positive interactions within them. In addition, other policy initiatives outside of the school setting could be implemented. Social programmes targeting family attitudes towards education could be designed. Conditional monetary transfers could alleviate the impact of a child's socio-economic status on his/her educational outcomes. Community campaigns which provide families with ways to support the academic life of their child at home could improve outcomes as well.

As the last point, it is worth mentioning that this analysis has certain empirical limitations. Some of the assumptions that were employed were plausible, others need further sensitivity analyses to prove their validity. Probably the strongest assumption used in this work is that missing values in the dataset are missing at random, although the more stringent assumption, missing completely at random, is not made. Missing at random assumption affects both the estimation of the coefficients and the inference of them. Furthermore, assumptions, such as the non-existence of multicolinearity, endogeneity, and omitted variables, are not always easily testable and affect as well the estimation of the parameters and their standard errors. A theoretical limitation of this study is that the association between cognitive and non-cognitive skills is assumed to be not directional. However, this assumption could easily be relaxed in further research.

To conclude, this study presents a first glance into the education process of cognitive and non-cognitive skills. Due to the aforementioned empirical limitations of the model, results should be interpreted as exploratory. The main purpose of this analysis is to expand the production of education and evaluation of education policies to incorporate non-cognitive development as a further main outcome. In this sense, a final recommendation is that assessments of non-cognitive skills and traits should be included as a part of school accountability.

References

Allison, D., (2003). MIssing data techniques for structural equation modeling. *Journal of Abnormal Psychology,* Volume 112, pp. 545-557.

Almlund, M., Duckworth, A., Heckman, J. and Kautz, T., (2011). *Personality psychology and economics,* Massachusetts: National Bureau of Economic Research.

Arbuckle, L., (1996). Full information estimation in the presence of incomplete data. In: R. Marcoulides, ed. *Advanced structural equation modeling.* Mahwah: Erlbaum, pp. 243-277.

Attanasio, O., Meghir, C., and Nix, E., (2015). *Human Capital Development and parental investment in India,* New Haven: Yale University.

Azubuike, B., and Briones, K., (2016). *Young Lives Rounds 1 to 4 Constructed files: Technical Note 35,* Oxford: Young Lives.

Bandura, A., (1982). Self-efficacy mechanism in human agency. *American Psychologist,* Volume 37, pp. 122-147.

Bandura, A., (1994). Self-efficacy. In: H. Friedman, ed. *Encyclopedia of human behaviour.* New York: Academic Press, pp. 71-81.

Banerjee, A. V., Cole, S., Duflo, E., and Linden, L., (2007). Remedying Education: Evidence from Two Randomized Experiments in India. *The Quarterly Journal of Economics,* 122(3), pp. 1235-1264.

Barnett, I., Ariana, P., Petrou, S., Penny, M. E., Galab, S., Woldehanna, T., and Boyden, J., (2012). Cohort profile: The young lives study. *International Journal of Epidemiology,* 42(3), pp. 701-708.

Barrick, M. and Mount, M., (1991). The Big Five Personality Dimensions and Job Performance: A Meta-Analysis. *Personnel Psychology,* 44(1), pp. 1-26.

Becker, G., (1964). Investment in human capital: a theoretical analysis. *Journal of Political Economy,* 70(5), pp. 9-49.

Bednar, R., and Petterson, S., (1995). *Self-esteem: Paradoxes and innovations in clinical theory and practice.* 2nd ed. Washington, DC: American Psychological Association.

Berger, L., Paxson, C., and Waldfogel, J., (2009). Income and child development. *Children and Youth Services Review,* Volume 31, pp. 978-989.

Berman, P. & McLaughlin, W., (1975). Federal Programs Supporting Education Change. *The Findings in Review,* Volume IV, pp. 1589-1594.

Bharadwaj, P., Løken, K. V., and Neilson, C. (, (2013). Early life health interventions and academic achievement. *The American Economic Review,* 103(5), pp. 1862-1891.

Boardman, A. Davis, O., and Sanday, P., (1977). A simultaneous Equation model of the educational process. *Journal of Public Economics*, Volume 7, pp. 23-49.

Boardman, A., Davis, O., and Sanday, P., (1973). A simultaneous equation model of the educational process: The Coleman data revisited with an emphasis upon achievement. *Amercian Statistical Association*, pp. 62-71.

Bollen, A. and Pearl, J., (2012). Eight myths about causality and structural models. In: L. Morgan, ed. *Handbook of structural modeling.* New York: Springer, pp. 301-328.

Boomsman, A., Hoyle, R., and Panter, A., (2012). The structural equation modeling research report. In: R. Hoyle, ed. *Handbook of structural equation modeling.* New York: Guilford, pp. 341-358.

Borga, L., (2015). *Children's own time use and its effect on skill formation,* Working Paper Series 534. Prague: CERGE-EI.

Bowles S. and Gintis H., (2000). Does schooling raise earnings by making people smarter?. In: Arrow K, ed. *Meritocracy and Economic Inequality.* Princeton: Princeton University Press, pp. 118-136.

Bowles, S., (1970). *Towards an educational production function.* s.l.: UMI.

Brackett, M., and Katulak, N., (2007). Emotional Intelligence in the Classroom: Skill-Based Training for Teachers and Students. In: J. Ciarrochi, ed. *Applying Emotional Intelligence: A Practitioner's Guide.* Hove: Psychology Press, pp. 1-27.

Brewer, D. & Hentschke, G., (2010). Theoretical Concepts in the Economics of Education. In: E. Eide, ed. *Economics of Education.* Provo: Brigham Young University, pp. 193-198.

Brunello, G., and Schlotter, M., (2011). *Non-Cognitive Skills and Personality Traits: Labour Market Relevance and Their Development in Education & Training Systems,* Discussion Paper No. 5743, Bonn: IZA.

Caprara, G., Barbaranelli, C., Steca, P., and Malone, P., (2006). Teachers' self-efficacy beliefs as determinants of job satisfaction and students' academic achievement: A study at the school level. *Journal of school psychology,* Volume 44, pp. 473-490.

Carneiro, P., Crawford, C., and Goodman, A., (2007). *The impact of early cognitive and non-cognitive skills on later outcomes,* London: Centre for the Economics of Education.

Coleman, J., (1966). *Equality of Educational Opportunity,* Washington D.C.: U.S. Government Printing Office.

Crampton, F., (2009). Spending on school infrastructure: does money matter?. *Journal of Educational Administration,* 47(3), pp. 305-322.

Cunha, F. and Heckman, J., (2008). Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation. *The Journal of Human Resources*, XLIII(4), pp. 739-782.

Cunha, F., and Heckman, J., (2007). The Technology of Skill Formation. *American Economic Review,* Volume 97, pp. 31-47.

Cunha, F., Heckman, J., and Schennach, S., (2010). Estimating the technology of cognitive and noncognitive skill formation. *Journal of Econometric Society,* 78(3), pp. 883-931.

Cunha, F., Heckman, L., Lockner, J., and Masterov, D., (2006). Interpreting the Evidence on Life Cycle Skill Formation. In: E. Hanushek, ed. *Handbook of the Economics of Education.* Amsterdam: North-Holland, pp. 697-812.

Davison, K., Werder, J., and Lawson, C, (2009). Children's Active Commuting to School: Current Knowledge and Future Directions. *Public Health Research, Practice, and Policy,* 5(3), pp. 1-11.

Do, D., (2009). *Mathematics Teaching and Learning in Vietnam,* Hanoi: Centre for Curriculum Development and Teaching Methodology, National Institute of Educational Sciences.

Downey, D., (1995). When bigger is not better: family size, parental resources, and children's educational performance. *American Sociological Review,* 60(5), pp. 746-761.

Duc, L. and Hang, T., (2016). *Inequality in Educational Opportunities and Outcomes: Evidence From Young Lives Data in Vietnam,* Oxford: Young Lives.

Duckworth, L., and Seligman, M., (2005). Self-discipline outdoes IQ in predicting academic performance of adolescents. *Psychological Science,* Volume 16, pp. 939-944.

Duflo, E., Pascaline, D. and Kremer, M., (2011). Peer Effects, Teacher Incentives, and the Impact of Tracking: Evidence from a Randomized Evaluation in Kenya. *American Economic Review,* Volume 101, pp. 1739-17774.

Enders, C., and Bandalos, D., (2001). The relative performance of full information maximum likelihood estimation for missing data in structural equation models. *Structural equation modeling,* Volume 8, pp. 430-457.

Field, E., Robles, O., and Torero, M., (2009). Iodine deficiency and schooling attainment in Tanzania. *American Economic Journal: Applied Economics,* pp. 140-149.

Figlio, D., Guryan, J., Karbownik, K., and Roth, J., (2014). The effects of poor neonatal health on children's cognitive development. *American Economic Review,* 104(12), pp. 3921-55.

Finney, J. and DiStefano, C., (2006). Nonnormal and categorical data in structural equation modeling. In: R. Hancock, ed. *A second course in structural equation modeling.* Greenwich: Information Age Publishing, pp. 269-314.

Flouri, E., (2006). Parental interest in children's education, children's self-esteem and locus of control, and later educational attainment: Twenty-six year follow-up of the 1970 British Birth Cohort. *The British Psychological Society,* Volume 76, pp. 41-55.

García, M., (2013). *What we learn in school: Cognitive and non-cognitive skills in the educational production function,* New York: Columbia University.

Gintis, H., (1971). Education, Technology, and the Characteristics of Worker Productivity. *The American Economic Review,* 61(2), pp. 266-279.

Glewwe, P. & Kremer, M., (2006). School, Teachers, and Education Outcomes in Developing Countries. In: E. a. W. F. Hanushek, ed. *Handbook of Economics of Education.* Amsterdam: North-Holland, pp. 945-1012.

Grafen, A. and Hails, R., (2002). *Modern statistics for the life sciences.* Oxford: Oxford University Press.

Greene, W., (2002). *Econometric Analysis.* 5th ed. New Jersey: Prentice Hall.

Gutman, L., and Schoon, I., (2013). *The impact of non-cognitive skills on outcomes for young people,* London: Institute of Education, University College London.

Gyimah-Brempong, K. & Gyapong, A., (1991). Characteristics of Education Production Functions: An application of Canonical Regression Analysis. *Economics of Education Review,* 10(1), pp. 7-17.

Hang, D., (2015). *Examining the Relation between "Socialization" Practices and the Quality of Primary School Student Learning in Vietnam?,* London: ESP Working Paper Series.

Hansen, K., Heckman, J., and Mullen, K., (2004). The effect of schooling and ability on achievement test scores. *Journal of Econometrics,* Volume 121, pp. 39-89.

Hanushek, E. and Kimko, D., (2000). Schooling, labor force quality, and the growth of nations. *American Economic Review,* 90(5), pp. 1184-1208.

Hanushek, E. and Rivkin, S., (2010). Generalizations about Using Value-Added Measures of Teacher Quality. *American Economic Association,* 100(2), pp. 267-271.

Hanushek, E., (1972). *Education and Race,* Washington D.C.: Lexington Mass.

Hanushek, E., (1979). Conceptual and Empirical Issues in the Estimation of Educational Production Functions. *The Journal of Human Resources,* 14(3), pp. 351-388.

Hanushek, E., (2003). The failure of input-based schooling policies. *Economic Journal,* Volume 113, pp. 64-98.

Hanushek, E., (2007). *Education Production Functions,* Stanford: Hoover Institution, Stanford University.

Hanushek, E., and Woessmann, L., (2008). The Role of Cognitive Skills in Economic Development. *Journal of Economic Literature,* 46(3), pp. 607-668.

Hanushek, E.., Kain, J., Markman J., and Rivkin, S., (2003). Does Peer Ability Affect Student Achievement?. *Journal of Applied Economics,* Volume 18, pp. 522-544.

Harter, S., (2015). International Encyclopedia of the Social & Behavioral Sciences. In: J. Wright, ed. *Handbook of Child Psychology.* s.l.: Elsevier Ltd, pp. 492-497.

Hattie, C., (2009). *Visible Learning: A Synthesis of Over 800 Meta-Analyses Relating to Achievement,* London: Routledge/Taylor and Francis Group.

Heckman, J. and Rubintein, Y., (2001). The importance of noncognitive skills: lesson from the GED testing program. *The American Economic Review,* 91(2), pp. 145-149.

Hedges, L., Layne, R. and Greenwald, R., (1994). Does money matter? A meta-analysis of studies of the effects of differential school inputs on student outcomes. *Educational Researcher,* Volume 23, pp. 5-14.

Heineck, G., & Anger, S., (2010). The returns to cognitive ability and personality traits in Germany. *Labour Economics,* 17(3), pp. 535-546.

Hogan, R., and Roberts, B., (2001). *Personality Psychology in the Workplace,* s.l.: American Psychological Association.

Hoyle, R., (2012). The model specification in structural equation modeling. In: R. Hoyle, ed. *Handbook of structural equation modeling.* New York: Guilford Press, pp. 126-144.

Huong, N., (2013). *Making Progress: Report of the Young Lives School Survey in Vietnam,* Hanoi: Young Lives.

Huong, N., (2014). *Young Lives Survey Design and Sampling in Viet Nam,* Hanoi: Young Lives.

Jerrim, J. and Vignoles, A., (2011). *Social mobility, regression to the mean and the cognitive development of high ability children from disadvantaged homes,* London: Institute of Education, University of London.

Johnston, D., Nicholls, M., Shah, M., and Shields, M., (2010). *Handedness, Health and Cognitive Development: Evidence from Children in the NLSY,* Discussion Paper No. 4774. Bonn: Institute for the Study of Labor.

Jones, M., and Rowley, G., (1990). What does research say about parental participation in children's reading development?. *Evaluation & Research in Education,* 4(1), pp. 21-36.

Jordan, C., Zeigler-Hill, V., and Cameron, J., (2015). Self-esteem. *International Encyclopedia of the Social & Behavioral Sciences,* 21(2), pp. 522-528.

Kaplan, D., (2000). *Structural Equation Modeling.* Thousands Oaks: Sage.

Kaplan, D., (2012). *Structural Equation Modeling: Foundations and Extensions.* 2nd ed. Thousand Oaks: SAGE Publications.

Kline, R., (2011). *Principles and Practice of Structural Equation Modeling.* 3rd ed. New York: Guildford Press.

Kniesner, T., and Ter Weel, B., (2008). Noncognitive Skills and Their Development. *Journal of Human Resources,* 43(4).

Krueger, A., (2003). Economic considerations and class size. *Economic Journal,* Volume 113, pp. 34-63.

Kruger, A., (1999). Experimental estimates of the education production function. *The Quarterly Journal of Economics*, 114(2), pp. 497-532.

Krugman, P., (2009). *Microeconomics.* 2nd ed. New York: Worth Publishers.

Lang, K., (1993). *Ability bias, discount rate bias ant the return to education,* Boston: Boston University.

Lee, S., (2007). *Structural Equation Modeling: A Bayesian Approach.* West Sussex: John Wiley & Sons Ltd.

Levin, H., (1980). Educational production theory and teacher inputs. In: B. Windham, ed. *The Analysis of Educational Productivity: Issues in Macroanalysis.* Cambridge: Ballinger Publishing Co., pp. 203-231.

Levin, H., (2012). *More than just test scores,* New York: Springer.

Levin, M., (2012). *The utility and need for incorporating noncognitive skills into large-scale educational assessments,* s.l.: The Role of International Large-Scale Assessments: Perspectives from Technology, Economy, and Educational Research.

Marsh, H., and Yeung, A., (1997). Causal effects of academic self-concept on academic achievement: Structural equation models of longitudinal data. *Journal of Educational Psychology,* Volume 89, pp. 41-54.

Mayo Foundation for Medical Education and Research, 2017. *Headaches in children.* [Online]

Available at: http://www.mayoclinic.org/diseases-conditions/headaches-in-

children/symptoms-causes/dxc-20201618
[Accessed 8th 8 2017].

Meghir, C. and Rivkin, S., (2011). *Econometric Methods for Research in Education. Working Paper W10/10,* London: Economic an Social Research Council.

Mehrotra, S., and DelaMonica, E., (1998). Household costs and public expenditure on primary education in fi ve low-income countries: A comparative analysis. *International Journal of Educational Development,* 18(1), pp. 41-61.

Mincer, J., (1958). Investment in human capital and personal income distribution. *Journal of Political Economy,* Volume 66, pp. 281-302.

Mincer, J., (1970). The distribution of labour incomes: a survey with special reference to the human capital approach. *Journal of Economic Literature,* 3(1), pp. 1-26.

Monk, D., (1989). The Education Production Function: Its Evolving Role in Policy Analysis. *Educational Evaluation and Policy Analysis,* 11(1), pp. 31-45.

Nguyen, N., (2008). *An Assessment of the Young Lives Sampling Approach in Vietnam: Technical Note 4,* Oxford: Young Lives.

Ngware, M., Oketch, M., and Mutisya, M., (2014). Does teaching style explain differences in learner achievement in low and high performing schools in Kenya?. *International Journal of Educational Development,* Volume 36, pp. 3-12.

Noftle, E. and Robins, R., (2007). Personality Predictors of Academic Outcomes: Big Five Correlates of GPA and SAT Scores. *Journal of Personality and Social Psychology,* 93(1), pp. 116-130.

Nuttal, E., Nutall, R., Polit, D., and Hunter, J., (1976). The effect of family size, birth order, siblings separation and crowding on the academic achievement of boys and girls. *American Educational Research Journal,* 13(3), pp. 217-223.

OECD, (2016). *Fostering and Measuring Skills: Improving Cognitive and Non-Cognitive Skills to Promote Lifetime Success,* Paris: OECD.

Orr, A., (2003). Black-White Differences in Achievement: The Importance of Wealth. *American Sociological Association*, 76(4), pp. 281-304.

Parcel, T. and Menaghan, E., (1994). Early parental work, family social capital, and early childhood outcomes. *American Journal of Sociology*, 4(972-1009), p. 99.

Psacharopoulos, G. and Patrinos, H., (2002). *Returns to Investment in Education: A Further Update,* Washington D.C.: The World Bank.

Psacharopoulos, G., and Patrinos, H., (2004). Returns to investment in education: a further update. *Education Economics*, 12(2), pp. 111-134.

Raykov, T. & Marcoulides, G., (2006). *A first course in Structural Equation Modeling.* 2nd ed. New Jersey: Lawrence Erlbaum Associates Publishers.

Raykov, T., and Marcoulides, G., (2011). *Introduction to psychometric theory,* New York: Taylor & Francis.

Resolution 90, CP on direction of and policy on education, health, culture socialization. *August 21, 1997.* s.l.: Hanoi.

Rigdon, E., (1994). Calculating degrees of freedom for a structural equation model. *Structural Equation Modeling,* 1(3), pp. 274-278.

Rivkin, S., (2010). Desegregation, Academic Achievement, and Earnings. In: *Economics of education - production of schooling.* Amherst: Elsevier Ltd., pp. 394-401.

Rolleston, C., and James, Z., (2015). *After Access: Divergent Learning Profiles in Vietnam and India,* London: Prospects: Quarterly Review of Comparative Education.

Rolleston, C., James, Z., Pasquier-Doume, L., and Tam, T., (2013). *Making Progress: Report of the Young Lives School Survey in Vietnam,* Oxford: Young Lives.

Sacerdote, B., (2011). Peer Effects in Education: How Might They Work, How Big are They, and How Much Do We Know Thus Far?. In: E. Hanushek, ed. *Handbook of the Economics of Education.* North Holland: Elsevier.

Schultz, C., (1990). The Adolescent Society Revisited. *Creative Sociology,* 18(1), pp. 3-12.

Schultz, T., (1963). Investment in human beings. *Journal of Political Economy,* 70(5), pp. 1-8.

Schunk, D., (1984). Self-efficacy perspective on achievement behavior. *Educational Psychologist,* 19(1), pp. 48-58.

Shunk, D., and Zimmerman, B., (2009). *Modeling and self-efficacy influences on children's development of self-regulation,* Cambridge: Cambridge University Press.

Sirin, S., (2005). Socioeconomic Status and Academic Achievement A Meta-Analytic Review of Res. *Review of Educational Research,* 75(3), pp. 417-453.

Smith, M., (1972). *Equality of Educational Opportunity: The Basic Findings Reconsidered.* New York: Random House.

Smith, T., (1999). *Self-efficacy, locus of control and the education production function,* Columbia: University of Missouri-Columbia.

Stata Corp, (2015). *STATA Structural Equation Modeling Reference Manual Release 14,* College Station,: Stata Press Publication.

Sutton, R., and Wheatley, F., (2003). Teachers' emotions and teaching: A review of the literature and directions for future research. *Educational Psychology Review,* Volume 15, pp. 327-358.

Todd, P. & Wolpin, K., (2006). *The Production of Cognitive Achievement in Children: Home, School and Racial Test Score Gaps,* Philadelphia: University of Pennsylvania.

Todd, P. and Wolpin, K., (2003). On the specification and estimation of the production function for cognitive of the production function for cognitive. *The Economic Journal,* Volume 113, pp. 3-33.

Tran, T. and Harpham, T., (2005). Primary education in Vietnam: Extra classes and outcomes. *International Education Journal,* 6(5), pp. 626-34.

Tschannen-Mora, M., and Hoy, A., (2007). The differential antecedents of self-efficacy beliefs of novice and experienced teachers. *Teaching and teacher education,* Volume 23, pp. 944-956.

Upton, G., and Cook, I., (2014). *A Dictionary of Statistics.* 2nd ed. Oxford: Oxford University Press.

Vandenberghe, V., (2010). Economics of Education. The Need to go Beyond Human Capital Theory and Production-Function Analysis. *Economics of Education,* 25(2), pp. 129-143.

Wagerman, S., and Funder, D., (2007). Acquaintance reports of personality and academic achievement: A case for conscientiousness. *Journal of Research in Personality,* Volume 41, pp. 221-229.

Warner, L., (1994). Social Class in America. In: B. Grusky, ed. *Social stratification: class, race and gender in sociological perspective.* Boulder: Westview Press.

Wilson, K., (2001). The Determinants of Educational Attainment: Modeling and Estimating the Human Capital Model and Education Production Functions. *Southern Economic Journal*, 67(3), pp. 518-551.

Wooldridge, J., (2013). *Introductory Econometrics: A Modern Approach.* 5th ed. South-Western: Cengage Learning.

World Bank, (2017). *World Bank Data.* [Online] Available at: http://data.worldbank.org/indicator/NY.GNP.PCAP.KD.ZG [Accessed 14th August 2017].

World Health Organization, (2008). *Training Course on Child Growth Assessment,* Geneva: World Health Organization.

Young Lives, (2011). *Young Lives School Survey,* London: UK Data Archive SN.

Young Lives, (2017). *Vietnam school survey*. [Online] Available at: http://www.younglives.org.uk/content/vietnam-school-survey [Accessed 02nd 08 2017].

Zeigler-Hill, V., (2012). The extended informational model of self-esteem. In: S. M. K. De Wals, ed. *Handbook of Psychology of Self-esteem.* New York: Nova Hauppauge, pp. 211-226.

Appendices

Appendix 1: Requirements for model identification

According to García (2013):

The order condition for identification implies that in any equation g in the system of equations ($g \in [1,\ldots,G]$ where G represents the total number of equations in the system), the number of excluded exogenous regressors is at least as large as the number of included endogenous variables.

$$K - K_g \geq M_g \quad (16a)$$

where K represents the number of exogenous regressors in the system, K_g represents the number of exogenous regressors included in equation g and M_g represents the number of included endogenous variables in equation g. This condition is a necessary, non-sufficient, condition for identification.

The rank condition (for the most parsimonious scenario, where there are two structural equations) implies that each equation is identified if (and only if) the second equation contains at least one exogenous variable that is excluded from the first equation (or, for a system with more than two equations, if each equation contains "its own" exogenous variable that does not appear elsewhere in the system).[115]

$$rank[\pi_g^*, \Pi_g^*] = rank[\Pi_g^*] = M_g \quad (16b)$$

This condition imposes a restriction on a submatrix of the reduced form coefficient matrix (Π). In the above equation, Π_g^* is the matrix of coefficients for the reduced form parameters for the excluded variables in equation g; π_g^* is one element of the submatrix; and M_g represents the number of included endogenous variables in equation g.

Appendix 2: General equation of structural equation model

According to Kaplan (2012):

$$\eta = \beta\eta + \Gamma\xi + \zeta\,,$$

where η is a m × 1 vector of endogenous latent variables, ξ is a k × 1 vector of exogenous latent variables, β is an m × m matrix of regression coefficients relating the latent endogenous variables to each other, Γ is an m × k matrix of regression coefficients relating endogenous variables to exogenous variables, and ζ is an m × 1 vector of disturbance terms.

Appendix 3: Young Lives study sites in Vietnam

The selected sites cover north, central, south, urban, delta, coastal and mountainous areas (Hang, 2015).

Source and elaboration: Nguyen, N., (2008). *An Assessment of the Young Lives Sampling Approach in Vietnam: Technical Note 4*, Oxford: Young Lives.

Appendix 4: Detailed statistic descriptive of mathematics and reading scores

Figure 4. Mathematics statistic descriptive

Raw score in Math Test

	Percentiles	Smallest		
1%	3	0		
5%	7	0		
10%	9	0	Obs	7,456
25%	12.5	0	Sum of Wgt.	7,456
50%	16		Mean	16.26448
		Largest	Std. Dev.	5.728609
75%	20	31		
90%	24	31	Variance	32.81696
95%	26	31	Skewness	.053862
99%	29	31	Kurtosis	2.831918

Variable	Obs	Mean	Std. Dev.	Min	Max
math	7,456	16.26448	5.728609	0	31

Figure 5.Reading statistic descriptive

Raw score in Language Test

	Percentiles	Smallest		
1%	2	0		
5%	7	0		
10%	8	0	Obs	7,424
25%	11	0	Sum of Wgt.	7,424
50%	15		Mean	14.7764
		Largest	Std. Dev.	5.087842
75%	18	29		
90%	21	29	Variance	25.88614
95%	23	29	Skewness	-.0961902
99%	26	29	Kurtosis	2.719354

Variable	Obs	Mean	Std. Dev.	Min	Max
reading	7,424	14.7764	5.087842	0	29

Appendix 5: Items used as indicators to measure self-esteem and self-efficacy

Table 5. Responses loading the highest with self-esteem

Items related to self-esteem	Factor Analysis	Cronbach's alpha
A lot of things about me are good.	0.59	0.64
Other people think that I am a good person.	0.52	0.59
When I do something, I do it well.	0.49	0.57
I can do things as well as most people.	0.48	0.60

Table 6. Responses loading the highest with self-efficacy

Items related to self-efficacy	Factor Analysis	Cronbach's alpha
I can usually handle whatever comes my way.	0.56	0.60
I am confident that I could deal efficiently with unexpected.	0.54	0.59
Thanks to my resourcefulness, I know how to handle unforeseen events.	0.53	0.58
I can remain calm when facing difficulties because I can resolve them.	0.49	0.55

Appendix 6: Distribution of students' responses to the items associated with self-esteem and self-efficacy

Table 7. Distribution of students' responses to self-esteem items

Items / Responses	A lot of things about me are good.	Other people think that I am a good person.	When I do something, I do it well.	I can do things as well as most people.
Strongly disagree	0.9%	0.9%	0.7%	2.4%
Disagree	22.4%	18.8%	22.4%	31.7%
Agree	72.3%	73.4%	70.3%	59.0%
Strongly agree	4.4%	6.9%	6.6%	6.9%
N	1,992			

Table 7 shows that for the first three self-esteem items students have respondent similarly. Around 70% of the students ‘agree’ with the statement, and a significant proportion (20%) ‘disagree’ with it. However, the last statement presents a different pattern of response, 60% of pupils ‘agree’ with it and 30% ‘disagree’.

Table 8. Distribution of students’ responses to self-efficacy items

Items / Responses	I can usually handle whatever comes my way.	I am confident that I could deal efficiently with unexpected.	Thanks to my resourcefulness, I know how to handle unforeseen events.	I can remain calm when facing difficulties because I can resolve them.
Strongly disagree	1.1%	2.5%	2.0%	0.9%
Disagree	32.7%	35.2%	39.3%	16.9%
Agree	60.7%	56.7%	55.2%	71.0%
Strongly agree	5.5%	5.7%	3.4%	11.2%
N	1,992			

Table 8 indicates that for the first three self-efficacy items students have respondent similarly. Between 55-60% of the students ‘agree’ with the statement, and a significant proportion (30%) ‘disagree’ with it. However, the last statement presents a different pattern of response, 70% of pupils ‘agree’ with it and only 15% ‘disagree’.

Appendix 7: Specification on the creation of parents and peer relation index

Table 9. Distribution of students' responses to items related to their relation with their parents

Items / Responses	I like my parents (3)	My parents like me (7)	My parents and I spend a lot of time together (10)	I get along with my parents (13)
Strongly disagree	0.6%	0.2%	1.7%	0.6%
Disagree	0.7%	1.4%	16.3%	10.1%
Agree	38.3%	43.4%	59.8%	66.5%
Strongly agree	60.5%	55.0%	22.2%	22.9%

Items / Responses	My parents understand me (19)	If I have children, I want to bring them up like I was (21)	My parents are easy to talk to (25)	My parents and I have a lot of fun together (29)
Strongly disagree	0.6%	0.8%	0.6%	0.7%
Disagree	7.3%	6.9%	11.0%	5.3%
Agree	61.9%	57.4%	67.0%	63.5%
Strongly agree	30.2%	35.0%	21.4%	30.5%

Figure 6. Stata output of Cronbach alpha results to create the parents' relation index

Item	Obs	Sign	item-test correlation	item-rest correlation	average interitem covariance	alpha
FEAY03R4	7596	+	0.5546	0.4142	.1282507	0.7987
FEAY07R4	7596	+	0.6455	0.5241	.1211263	0.7841
FEAY10R4	7596	+	0.6581	0.5037	.1150009	0.7880
FEAY13R4	7596	+	0.6675	0.5400	.1174743	0.7813
FEAY19R4	7592	+	0.7004	0.5792	.114175	0.7753
FEAY21R4	7596	+	0.6063	0.4536	.1215645	0.7946
FEAY25R4	7596	+	0.6741	0.5484	.1169243	0.7800
FEAY29R4	7592	+	0.7118	0.5987	.1141318	0.7727
Test scale					.1185808	0.8062

Table 10. Distribution of students' responses to items related to their relation with their peers

Items / Responses	I make friends easily (2)	I am popular with kids of my own age (9)	Most other kids like me (12)	Others kids want me to be their friend (16)
Strongly disagree	1.4%	2.3%	3.5%	1.0%
Disagree	17.9%	46.6%	47.6%	19.3%
Agree	67.1%	46.6%	44.6%	72.2%
Strongly agree	13.7%	4.5%	4.3%	7.4%

Items / Responses	I have more friends than most other kids (20)	I have lots of friends (24)	I am easy to like (31)	I get along with other kids easily (34)
Strongly disagree	2.0%	0.7%	0.4%	0.4%
Disagree	44.9%	19.9%	23.4%	14.1%
Agree	45.9%	69.4%	70.4%	74.0%
Strongly agree	7.3%	10.0%	5.8%	11.6%

Figure 7. Stata output of Cronbach alpha results to create the peer relation index

Item	Obs	Sign	item-test correlation	item-rest correlation	average interitem covariance	alpha
FEAY02R4	7692	+	0.5304	0.3419	.0874567	0.7097
FEAY09R4	7692	+	0.5661	0.3795	.0844175	0.7022
FEAY12R4	7692	+	0.6218	0.4439	.0796023	0.6881
FEAY16R4	7692	+	0.5537	0.3933	.0867836	0.6987
FEAY20R4	7692	+	0.6370	0.4574	.0779772	0.6851
FEAY24R4	7684	+	0.6134	0.4588	.0820305	0.6856
FEAY31R4	7692	+	0.5746	0.4229	.0856513	0.6934
FEAY34R4	7688	+	0.5724	0.4222	.0859257	0.6937
Test scale					.0837306	0.7223