Age-dependent Human Capital Investments and Socio-Economic Outcomes

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To

Elvira Reuß

Klaus Reuß, in memoriam

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1. Introduction

1.1 Motivation

The most important resource of Germany and most other modern economies today is human capital and knowledge. Human capital enables individuals to be productive in the knowledge society and to generate economic growth, but also to contribute to society and health. Human capital is usually determined by various skills that are often grouped into cognitive and noncognitive skills. Cognitive skills refer to reasoning skills, problem solving skills or literacy. Noncognitive include personality traits such as conscientiousness, persistence, adaptability and many others.

Skill development can be improved by education. Education starts in the cradle and continues until old age. From an economic point of view, education can be seen as an investment that produces skills that in turn generate human capital and social outcomes. The nature of investments changes during the course of life. In the cradle an investment may be the smile of the mother and other aspects of the mother-child dyad. During childhood it may relate to parents teaching and motivating the child and the family environment. During adolescence investments may stem from schooling and peer relationships and in adult age from university and the labour market.

Economists have addressed educational strategies that help fostering human capital. In particular, the conditions early in life seem to be important as skills become more and more stable during childhood and adolescence. Time windows, critical and sensitive periods, may exist when an investment has to occur to be effective. It is possible that missed opportunities to invest cannot be compensated during later periods. When are those time windows for different skills? Can later investments complement early investments?

This dissertation aims at providing a better understanding of those patterns. Education policy-makers, parents and teachers require more and better information that covers wider socio-economic, linguistic and cultural contexts before comprehensive action plans can be developed to enhance human capital. Education can not be analysed independently, it is related to the structure and income of the society, the labour market, the family environments and the demographic composition. What types of investments are the most efficient? How do early and late investments influence the development of human capital over the life-cycle? What increase in lifetime earnings can be expected from an investment? How do returns on investments depend on the labour market? When should resources be directed into education? What is the role of education in an ageing society?

Another issue is the relationship of social inequality and heterogeneous investments in education. Inequality can exist in several dimensions, such as wage inequality, inequality in social status, in health, in life satisfaction or in knowledge. Thus, investing in skills may not only help to increase economic growth, but also help to reduce inequality in the society. When do investments have to occur to yield significant inequality reduction? Under which conditions is it reasonable to invest into the low skilled and when should the high skilled be supported?

The dissertation will give some preliminary answers to these questions based on a simulation model and an empirical approach for Germany and Europe.

1.2 Data and Methods

Several strategies are used in this dissertation to address the questions described above. A simulation model of life cycle skill formation is employed to investigate the relationship of investments with the labour market, the society and the population structure. To investigate the multiplicty of skills and investments for Germany, various statistical methods such as ordinary least squares regression, cluster analysis, factor analysis and partial least squares regression are applied.

The underlying framework in all chapters is the technology of skill formation[1], a CES-production function that produces skills of the current period out of skills and investments of the previous periods. The simulation model adopts this function and extends it to an 80 period life cycle specification with each period representing one year of life. Two learning multipliers, one cognitive and one noncognitive as well as age related skill depreciation are added. Those variables are used to model age-dependent neurobiological aspects of the life course. The stock of skills and the current investments are not the only determinants of human capital. The process of aging may eventually be stronger than all accumulation processes and stop human capital formation. On the other hand

[1] Cunha, F. and J. J. Heckman (2007), The Technology of Skill Formation, The American Economic Review, 97 (2), 31-47.

the rapid brain growth in infancy could provide multiple chances to invest that do not exist in other periods.

The model is calibrated for Germany and Europe with data from several sources. The PISA (Programme for International Student Assessment) distributions of the OECD publications are used to generate distribution of investment. Data from the Federal Statistical Office of Germany, OECD.stat and Eurostat provide several labour market variables (income, earnings inequality), demographic information as well as information on the pension system.

After calibration the model simulates the skills and the human capital for a German (European, respectively) population in the education system and the labour market. Individuals are modeled from birth until death. Investments in education can be performed at any point of the life cycle for any individual. The individuals maximize their accumulated, discounted lifetime earnings. In an extension the models also take into account demographic trends in Germany until the year 2080. Individuals reproduce and educate their children. It attends the challenges of demographic change and the expected increase in the old- age-dependency ratio. All in all, the model provides a tool to assess different polices that may aim at redistribution, income maximization or stabilizing pensions.

The technology of skill formation is estimated in the second part of the dissertation. For this the Mannheim Study of Children at Risk (MARS) is used, a longitudinal epidemiological cohort study following infants at risk from birth to adulthood. The individuals were born between February 1986 and February 1988. Medical and psychological examinations elevating environmental aspects, skills, personality and social outcomes were assessed in different research waves. They took place when the children were 3 months, 2, 4.5, 8, 11, 15 and 18 years old and are still going on.

The data provides the possibility to estimate the technology of skill formation for each of the research waves separately. As the data contains eleven different skills that are sometimes highly correlated a factor analysis is employed to reduce their diversity to a few latent factors. They represent cognitive, mental and emotional skills with the two latter being noncognitive. The factors are used to estimate the skill production processes and possible critical and sensitive periods.

A rich set of psychometric measures regarding the socio-emotional environment is assessed in the second paper dealing with MARS. It includes the family environment, parental characteristics, the early mother-child interaction and many other aspects. A partial least squares regression is employed to identify latent factors behind the multiple correlated environmental aspects that best predict the skills of the subsequent period. Eventually, the predictive power of each environmental component can be calculated. This could help policy makers, teachers and parents to design investments and interventions.

1.3 Results

The simulation model for Germany finds the returns to investments to be higher the earlier they are made as a result of the cumulative nature of skill formation. Even though investments in cognitive skills at an early age seem more important than investments in noncognitive skills, both types of investment complement each other and both are necessary. In later adolescence und during adulthood investments in self-regulatory skills are more profitable. If the society aims at maximizing the sum of additional human capital, scarce resources should be invested in students from an advantageous environment or with above-average learning abilities. If the goal is instead to maximize the relative returns for each individual limited resources for additional educational investments should rather be given to the most disadvantaged.

An application of the simulation model on the European populations and economies confirms the results found for Germany. Investments need to be directed more generally to people of younger ages in Europe. It discusses how policy outcomes change as a result of unification processes in Europe. The chances to reduce interpersonal income and education inequalities generally increase. If the preferences of the society for equality are sufficiently large additional investments should specifically be directed to disadvantaged individuals during childhood.

An integration of the German pension system and the simulation of the demography in Germany into the skill simulation model yields additional results. If the goal of society is to reduce lifetime earnings inequality within one generation, preventative investments into human capital until the age of 17 and remedial financial transfers at later ages are the optimal strategies. As skills become more and more stable during the life cycle (increasing self-productivity) preventative policies are most effective the earlier they start. In the intergenerational dimension additional tax financed educational investments starting in 2011 for the newborns will have beneficial effects for the cohorts born after 1976 through higher pensions. The individuals who pay the tax experience an increase in their lifetime earnings, even though they finance the investments.

The study of the MARS data identifies three groups of skills: cognitive, mental and emotional skills. As the heterogeneity among noncognitive skills is higher, statistical analysis suggests a distiction of two noncognitive abilities. For all skills the impact of parental investments on cognitive and mental skills is found to be decreasing over time. Inequality at birth persists during childhood, especially due to the long-term to the adverse impacts of organic risk. Thus, improving maternal health during pregnancy and parental investments in infancy can yield large benefits for cognitive and mental development later in childhood.

The partial least squares approach identifies the mother-child interaction during infancy an additional important determinant of skill formation. To a lesser extend the home environment, parental characteristics and breastfeeding also play a role. Between the ages of 2 and 4.5 years cognitive skills can be enhanced by providing appropriate play materials and complementing parental support of child play. Parents supporting to learn numbers, shapes or letters seem to have a positive impact. Personality rather tends to be linked to the parent-child relationship. Persistence and mood can be improved by motivating and supporting the child, promoting independence and setting reasonable limits. The emotional trait "mood" is enhanced by praising the child, toys, owning a pet and making trips. Early investments are the most important but should be complemented by investments in late childhood to unfold their benefits. These results could help policy makers and educators to better design investments.

To sum up, the dissertation provides various insights in the human capital formation in the society, in infancy, in the home environment and in national and international contexts.

1.4 Structure

The dissertation at hand consists of five parts. Each chapter is an indepent paper written on my own or with the help of co-authors between 2008 and 2011 during my time at the Centre for European Economic Research (ZEW). The dissertation consists of two major parts. The chapter two, three and four are based on the simulation model. The fifth and sixth chapters contain the empirical examination of the MARS data.

The work presented in chapter two "Age-dependent Skill Formation and Returns to Education" is a joint work with Friedhelm Pfeiffer, who had the idea of developing a simulation model for the technology of skill formation and launched my research on human skill formation. The model we developed together in this part is also the fundament of chapters three and four. It was published in "Labour Economics". We extended the model to the European dimension and added several improving features and published chapter three "Human Capital Investment Strategies in Europe" as a ZEW Discussion paper. This paper has also been sent to a journal and is awaiting revision. Based on this research I combined the skill formation model with a simulation of the German demographic trends to model the relationships of skill formation with the ageing society, the labour market and the German pension system. The results of this research are presented in the third part "Preventative and remedial policies to reduce lifetime earnings inequality in Germany".

The second major part consists of the two papers "The Role of Parental Investments for Cognitive and Noncognitive Skill – Formation-Evidence for the First 11 Years of Life", presented in chapter five, and "Determinants of personality and skill development in the Socio-emotional environment during childhood", presented in chapter six. Chapter five is joint work with Manfred Laucht and Katja Coneus. Manfred Laucht from the Central Institute of Mental Health is the head of the MARS that started in 1986. Katja Coneus introduced me to the MARS data at the ZEW and we developed an estimation strategy to deal with the data together. We published the paper in "Economics and Human Biology". After splitting up the skill dimension in chapter five, chapter six additionally splits up investment dimension. This paper is the most recent part of my research.

2. Age-dependent Skill Formation and Returns to Education

This part is joint work with Friedhelm Pfeiffer and is published in Labour Economics 15 (4), 631-646.

Abstract:
This study investigates the distribution of returns to investments in cognitive and self-regulatory skills over the life cycle. In our simulation model, the distribution of returns to education results from the interaction of neurobiological and socioeconomic factors in age-dependent skill formation. A novel feature of our extension of the technology of skill formation (Cunha and Heckman 2007) is a life-span model that integrates skill depreciation at older ages and calibrates it to German data. Our evidence quantitatively illustrates the role early childhood plays in the shaping of human capital formation, inequality and economic growth.

Keywords: Intelligence, self-regulation, human capital, returns to education, life cycle.

JEL-classification: J21, J24, J31

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> "If a picture (graph) is worth a thousand words, then a model is worth a thousand pictures (graphs)",
> F. Cunha, J. J. Heckman, L. Lochner, D. V. Masterov (2006, p.704).

2.1 Introduction

Economists are interested in the formation of human capital over the life cycle. Since deep-seated skills are created early in the human developmental process (Amor 2003, Heckhausen and Heckhausen 2006, Heckman 2007, among others), the technology of skill formation (Cunha and Heckman 2007) and the life-cycle pattern of optimised investment receive a great deal of attention. The formation of cognitive skills, such as intelligence, memory power and reasoning, and self-regulatory skills, such as motivation, delay of gratification and persistence, begins in early childhood. The level of these skills is decisive for becoming a productive member of society. Feedback effects from the labour market are important to understand the investment processes and the complex patterns of life-cycle skill formation.

Reliable, representative, longitudinal data for analysing the returns on investments in cognitive and self-regulatory skills during early childhood is still scarce (see the interpretation of the evidence by Cunha et al. 2006; severe deprivation in the first month of life has long-lasting negative effects on the baby's cognitive development; see Beckett et al. 2006). Given the lack of longitudinal data, our contribution to the literature is the development of a model of cognitive and self-regulatory skill formation over the life cycle and a calibration of the model for a group of seven types of individuals based on German data.

Our model augments the technology of skill formation (Cunha and Heckman 2007) with three novel features. First, we model age-dependent cognitive and self-regulatory skill formation, and human capital accumulation together with age-dependent skill depreciation, over a life span of 80 years. Second, the model captures biological as well as social reasons for heterogeneity in skill formation. Two different learning multipliers, one for cognitive and one for self-regulatory skills, and age-specific skill deprecation rates are introduced. The parameters of the model are calibrated so that the simulated life-cycle pattern of skills and the human capital fit empirical data. For example, the heterogeneity of human capital in the group of seven individuals and its persistence starting early in the life cycle is simulated to replicate wage inequality in Germany (see Gernandt and Pfeiffer 2007). Third, we quantitatively illustrate the heterogeneous returns on age-specific investment in human capital over the life cycle depending on the amount of investment, the time pattern and differences in individual abilities. Institutional factors of the labour market that influence incentives for and returns on educational investment and the distribution of wages are considered. Thus, the paper deepens the understanding of the returns on age-specific human capital investment over the life cycle and its consequences for growth and inequality.

The paper is organized as follows. The next section elaborates on the ingredients of the simulation model of skill formation. In section 2.3, the essential heterogeneity in skills, their formation over the life span and the calibration of the model's parameters are introduced. Section 2.4 discusses findings from the simulated relationship between the technology of skill formation and the heterogeneity of returns to education over the life cycle. Section 2.5 concludes.

2.2 A Model of Skill and Human Capital Formation

2.2.1 Cognitive and Self-regulatory Skill Formation over the Life Cycle

There are two equations, one for cognitive skills, S_t^C, and one for self-regulatory skills, S_t^N, that specify skill formation and depreciation on a yearly basis over a life span of 80 periods (years) (see equation 2.1). Given a certain amount of investment, an average 70-year-old is not able to enhance her skill level as much as a 5-year-old, even though she might have a much higher skill level complementing the investment. In order to reflect age-dependent biological, social and psychological processes, we add two learning multipliers determining the person's learning aptitude, one for cognitive, l_t^C, and one for self-regulatory skills, l_t^N, respectively. The learning multipliers (figure 2.1) depend on age in a way that we regard as consistent with neurobiological and psychological findings from the child development literature (Borghans et al. 2008, Knudsen et al. 2006, Amor 2003, among others). While most of cognitive skill formation seems to be completed early in life, self-regulatory skills have a higher degree of plasticity in adolescence and over the life span. Therefore, the self-regulatory learning multiplier is lower than the cognitive one in early childhood and becomes higher in early adolescence.

The basic structure of the equation for the development of skills is:

$$S_t^k = \psi^k \cdot l_t^k \cdot \left\{ \frac{1}{3}(S_{t-1}^k)^\alpha + \frac{1}{3}(S_{t-1}^j)^\alpha + \frac{1}{3} \cdot \omega^k (I_t^k)^\alpha \right\}^{\frac{1}{\alpha}} + (1-\delta_{t-1}) \cdot S_{t-1}^k \tag{2.1}$$

with $k=C,N$ and j=C if $k=N, j=N$ if $k=C$ and $S_t^k \geq 0$.

The first term represents skill formation as a CES production function (Cunha and Heckman 2007). Next period skills are produced by both types of skills and investment, where α determines the degree of complementarity among skills and investment. ψ^k is an adjustment factor for the measurement units used to evaluate skills. ω^k represents an individual's ability to transform investments into skills. It is set to a value of one for the standard individual (a standard individual is assumed to have a median level of skills, achievement scores and earnings). We assume that each factor in the skill production function adds to new skills with the same weight of 1/3, which is in line with evidence provided by Cunha and Heckman (2008) for a production function similar to the first term of equation (2.1) (without the depreciation term). Validity of our assumptions is tested by computing six elasticities of investment in cognitive and self-regulatory skills for *a*=0 (see section 2.3.1. for discussion on *a*). We receive comparable values to the elasticities in Cunha and Heckman (2008) (see Tables 2.1 and 2.2). In fact, the elasticities used to simulate our model do not differ significantly from their empirical values (in the sense that they are in the 95 percent confidence intervals; note that in our model the ability and education of the mother is part of the investment).

The second part of equation (2.1) describes skill losses. Depreciation of skills is modest in childhood and accelerates with increasing age. Assuming a life expectancy of 80 years, the equation for the depreciation process is:

$$\delta_{t-1} = \frac{1}{as \cdot (81-t)}, \qquad (2.2)$$

where *as* is a parameter introduced to govern the dynamics of deprecation. If *as* is larger than 1, skill deprecation accelerates towards the end of the life span. In the last period, the individual loses all skills and dies. For our simulation, we use *as*=5.85 (see section 2.3.1. below). In that case, equation (2.1) implies self-productivity ($\frac{\partial S_{t+1}^k}{\partial S_t^k} > 0$; this is true for $as > 1$) and direct complementarity ($\frac{\partial^2 S_t^k}{\partial I_t^k \partial S_{t-1}^j} > 0$) resulting from the CES production function as long as $\alpha < 1$ (for a general discussion of these two concepts see Cunha and Heckman 2007).

2.2.2 Achievement Scores and Human Capital

We introduce another equation that explains the achievement an individual is able to reach in performing a task as a function of her cognitive and self-regulatory skills. Both skills are necessary to successfully complete the task and may interact for measured achievement tests in complex ways. A person with a high level of cognitive skills could produce low results if her motivation is low. Several test procedures measure student performance in reading, mathematics and natural sciences.

We model the achievement by means of a Cobb Douglas function with equal weights for cognitive and self-regulatory skills[2]:

$$\mathrm{A}_t = \psi_A \cdot \sqrt{\mathrm{S}_t^C \cdot \mathrm{S}_t^N} \tag{2.3}$$

The factor ψ_A is an adjustment factor for different normalizations of achievement scores and their respective distributions. We calibrate our model to the PISA 2000 reading test score distribution for Germany, A_{16} (OECD 2000). In this distribution, the ratio of the 90th to 10th percentile is 1.7 (= 620/363). In fact, the heterogeneity of skills might be higher in Germany, such that this is a conservative assessment. For example, the ratio of the 90th to 10th percentile of consumption expenditures available for children up to the age of six (which should be regarded as an indicator of investment rather than skill) is 2.6 for Germany (10,344 € to 3,900 €, see Pfeiffer and Reuß 2008). Table 2.4 sums up the parameter variations that cause the PISA distribution on the basis of equation (2.3) for seven percentiles and three scenarios.

Human capital in a given year is modelled as a function of cognitive and self-regulatory skills and the stock of human capital available from the previous year taking into account that human capital may accumulate or depreciate; for example, due to technological progress. Hence

$$H_t = \psi_H \cdot \left(S_{t-1}^{C\;\gamma\cdot\frac{1}{3}} \cdot S_{t-1}^{N\;\gamma\cdot\frac{1}{3}} \cdot H_{t-1}^{\;\gamma\cdot\frac{1}{3}} \right) + (1-\delta_{t-1}^H) \cdot H_{t-1}, \tag{2.4}$$

where S_t^C and S_t^N are defined in equation (2.1).

Human capital depreciates according to $\delta_t^H = \theta_H \cdot \delta_t$, where θ_H is a parameter that may vary among individuals, jobs, industries or over time. A high value of θ_H induces an early human capital maximum (e.g., in sports); a small θ_H, a later maximum (as for example in science). For the standard individual the average human capital maximum for Germany (*t*=52, cp. Franz 2006) is used, see figure 2.5. The parameter γ determines the transformation of skills into human capital that depends on labour market characteristics. For $\gamma = 1$, the heterogeneity of skills is transformed 1:1 into heterogeneity of wages and human capital. For values greater than 1, the heterogeneity of wages exceeds that of skills (such as in countries with large wage inequalities, for example Brazil or India), and for values smaller than 1 the reverse is true (e.g., in communist countries).

[2] Duckworth and Seligman (2005), for example, provide evidence that self-discipline is at least as important as the IQ in predicting academic performance.

2.3 Neurobiological and Socioeconomic Heterogeneity in Skill Formation

2.3.1 The "Standard" Individual

Cognitive and self-regulatory skills evolve according to equation (2.1) above for 80 periods. The parameter ψ^k (with *k*=*C, N*) is adjusted so that the level of cognitive skills at the age of 20 is $S_{20}^C = 600$. Furthermore, we set $\alpha = 0$ which implies a Cobb Douglas function of skill formation. The evidence of Cunha et al. (2008), based on data from the United States, suggests a slightly higher degree of complementarity (the point estimates are -0.12 for cognitive and -0.25 for non-cognitive skills). The simulation results, based on values between 0 and -0.2, do not greatly change our conclusion (see Pfeiffer and Reuß 2007). Therefore, and because there is a confidence interval around the point estimates, we decided to present the results based on $\alpha = 0$. The factor *as* is adjusted in a way such that the value of S_{65}^C in equation (2.1) is 87 percent of S_{20}^C (that is, *as*=5.85). There is evidence in the literature that fluid problem-solving skills decrease over the life cycle in a similar way (Kaufman et al. 1996, among others). Our standard individual's cognitive skills start at a value of 180 ($S_0^C = 180$), which is 30 percent of the skill level at age 20. This calibration is motivated by evidence on the brain volume of newborns, which is about 25 to 30 percent of the brain volume at a young adult age (Courchesne et al. 2000), as well as by evidence on the information processing speed of four-year-old children, which is about 35 percent of that of adults (Kail 2000). We do not, however, argue that there is a constant or perfect correlation between brain volume and cognitive skills, since skill formation over the life cycle also depends on investments.

The standard individual beginning at the age of 18 chooses the optimal amount of (symmetric) investment in cognitive and self-regulatory skills; i.e., the amount that maximizes his discounted amount of lifetime human capital. The price of one unit of tertiary education in both skills is set at 10,613 € annually (this value equals the OECD 2007 calculation for per capita expenditures of tertiary education in Germany). Hence:

$$I_t^{k*} = \arg\max\left(\sum_{t=18}^{65} \frac{H_t(I_{t-1,t-2,\dots}^{C*}, I_{t-1,t-2,\dots}^{N*}) - (I_t^{C*} + I_t^{N*}) * 0.5 * 10,613}{(1+i)^{t-18}}\right). \tag{2.5}$$

Figure 2.2 shows the optimal amount of investment in adult life. For the standard individual, the resulting level of cognitive and self-regulatory skills over the life cycle is illustrated in Figure 2.3. It replicates psychological findings on the development of cognitive skills and intelligence (see

Courchesne et al. 2000, Caspi et al. 2005, West 2005), as well as findings on the development of self-regulatory skills and social integration over the life span (see Heckhausen and Heckhausen 2006, Achtziger and Gollwitzer 2006, Roberts et al. 2003). Cognitive skills peak in young adult age, self-regulatory skills at middle age. If we adjust ψ_A in (2.3) so that A_{16} equals 507.77 (the PISA reading test value in Germany for the 50th percentile (OECD 2000)), the decline of cognitive skills (from equation (2.3)) in later adulthood is compensated by rising self-regulatory skills, so that achievement remains on a high level over the life span (see Figure 2.4).

In Germany, the average annual earnings of a full-time worker in industry are 29,787 € (Federal Statistical Office Germany 2006). If we assume that an individual works from period 18 to period 65, lifetime earnings are around 1,400,000 €. The parameter ψ_H in (2.4) is adjusted to satisfy this condition. Furthermore, ϑ^H in (2.4) is adjusted, so that the human capital maximum is reached at t=52. The evolution of human capital over the life cycle of our standard individual is depicted in Figure 2.5.

2.3.2 A Population of Heterogeneous Individuals

For the purpose of calibration, a population of seven heterogeneous individuals representing seven percentiles from the 4,432 unique observations of the PISA 2000 (OECD 2000) reading test scores for German students are used (cf. Table 2.3). Table 2.4 sums up the parameter variations that cause the PISA distribution on the basis of equation (2.3) for these seven percentiles and for three types of (essential) heterogeneity:

- Heterogeneity stemming from differences in the amount of investments that individuals receive as a consequence of their socioeconomic environment from period 0 to period 80.
- Heterogeneous ability to transform investments into new skills, keeping investment fixed.
- Heterogeneity in initial conditions, S_0^k, which may result from differences in prenatal conditions, for example, holding ability and investment constant.

For instance, a student at the 99th percentile of the PISA test score distribution receives ceteris paribus skill investments that are 2.7684 times higher than someone at the 50th percentile, defined as the standard individual (column 2, Table 2.4). The learning ability of a student at the 99th percentile will be, ceteris paribus, 1.4 times higher than that of the standard individual (column 3, Table 2.4). Figure 2.6 illustrates the level of cognitive and self-regulatory skills, achievement and human capital for a simulated population receiving heterogeneous skill investments during childhood on an annual basis. Even though idiosyncratic shocks during the working life may have a significant impact on human capital formation (Krebs 2003), the expected lifetime income will still mainly depend on conditions in early life, as long as randomness in adult age is not arbitrarily large.

The heterogeneity in human capital is calibrated by the adjustment of γ and ψ_H in (2.4) to the empirical wage distribution in Germany (according to Gernandt and Pfeiffer (2007) the ratio of the 90^{th} to the 10^{th} percentiles (hereafter referred to as the 90:10 ratio) of the wage distribution roughly equals 3 in 2005). Inequality in the level of human capital can result from inequality in skills at the age of 18, educational investments during adulthood and differences in labour markets characteristics. Due to skill complementarity, the optimal amount of educational investment during adulthood rises with the level of skills previously acquired.

2.4 Simulation Results

2.4.1 Returns to Symmetric Investments in Skills

This chapter discusses the simulation results for the returns to education at different ages during childhood and young adult age. It is assumed that the seven individuals of our heterogeneous population work from the age of 18 until the age of 65. The amount of human capital of each individual is defined as the present value of the cumulated annual earnings evaluated at the age of 18. The interest rate is assumed to be 2 percent. We calculate individual returns to education as the percentage change in the present value of accumulated lifetime income at period 18 due to additional age-dependent investments during childhood.

An exogenous increase in investments (for example, by the government) may cause families to reduce their investments, causing crowding out. Crowding out of government investments depends mainly on socioeconomic patterns and the design of an intervention. There will only be little crowding out if an intervention is not anticipated and additional investments complement current investments, and vice versa (see Das et al. 2004, Hong-Kyun 2001, among others). Investments often increase the resources of a mother or a family or result in other positive changes in the environment. Thus quantifying crowding out is complicated. Our focus is a different one: the returns to education in our model rather illustrate the potential that optimally designed investments can have as a function of age and previously acquired skills. The optimal design is a different issue.

We define an investment impulse as an additional investment ($I_t^k = 5, k = C, N$) at certain stages of childhood: from periods 0 to 5 (preschool investment impulse), from periods 6 to 11 (primary impulse), from periods 12 to 17 (secondary impulse) and from periods 18 to 21 (tertiary impulse). The tertiary educational impulse is specific in the sense that individuals have to sacrifice four years of income in order to obtain this level of education. The cost (in euros) of an annual investment impulse is 5,627 (which corresponds to the per capita costs of the German education system in 2005 reported in OECD 2007).

Table 2.5 reports the resulting returns on investments for an essential heterogeneity of type one. Higher learning multipliers l_t^k in young age make early skill investments more profitable. Individuals from more disadvantaged environments receive lower absolute increments of human capital even though their (relative) returns are always higher. Those starting with a relatively low skill level benefit little from an additional investment impulse in terms of additional monetary earnings (see Table 2.5). These results suggest that if society is interested in maximizing the total amount of human capital, additional scarce resources should ideally be invested in children that grew up in a stimulating environment. However, the relative gains (the additional earnings in percent of actual earnings) are significantly higher for individuals from disadvantaged environments (see Table 2.5). This is due to decreasing marginal rates of return to additional investments if only one exogenous factor in the skill production function is increased while keeping all others constant. Thus, if society is interested in maximizing the relative gains in human capital, it follows that additional scarce resources should ideally be invested in children from disadvantaged environments.

With increasing age, the costs of education become higher than the benefits. Thus, for a tertiary educational investment, not the 1st but the 25th percentile receives the highest individual returns. The 1st percentile has a benefit that is smaller than the costs, because the low skill level does not complement the investment in tertiary education. Thus the lowest percentile faces a negative return to tertiary education. The 25th percentile receives the highest individual educational return in this scenario. Not only is the benefit significantly higher than the cost of education, but also the level of skills is still small enough to generate a high individual rate of return.

Table 2.6 contains the results for the case when individuals differ, ceteris paribus, with respect to their ability of transforming a given educational input into new skills, ω^k . For this case of essential heterogeneity type two, our individuals do not differ with respect to home environment and investment. Decreasing marginal rates of education do not play a role in this scenario, since the population of the seven individuals is exposed to absolutely identical amounts of inputs. Our findings suggest that the absolute and relative returns on age-dependent investments increase with giftedness. An investment in education has the highest returns for gifted individuals and returns become lower or even negative for the others. Thus, differences in individual giftedness have a higher impact on human capital inequality than differences in environment. This is a result of self-productivity in the technology of skill formation. These findings have important implications for compensating policies. If the essential source of heterogeneity stems from differences in ability rather than from differences in environments, it follows that for successful compensation policies more resources will be needed.

It is possible that investments in skills are not symmetric. Due to the differences in learning multipliers, investments in cognitive skills during early childhood have the highest long-run impact. In adolescence and young adult age, however, self-regulatory skill investments become the preferred type of investment. In that case schools, for example, may play an important role specifically for the formation of self-regulatory skills (cf. Heckman 2000).

2.4.2 Individual Giftedness and Social Environment

Presumably, heterogeneity stemming from different environments and abilities will arise simultaneously. To assess rates of return for this case, we study a model variant with a population of individuals whose heterogeneity of skills is explained in equal parts by social environment and giftedness. The new population consists of 49 heterogeneous individuals whose respective skills correspond to all possible combinations of environmental influences and individual giftedness. Table 2.7 depicts the absolute monetary and the individual relative returns to education of the primary school impulse for this population. The highest returns measured in absolute monetary units are achieved by the most gifted individuals; i.e., by those who received the highest environmental investments. However, the highest individual returns to an educational impulse are achieved by very gifted individuals from disadvantaged environments.

2.4.3 Optimal Duration of Tertiary Education

Next, we investigate the decision of choosing the optimal duration of tertiary education. Individuals maximize their returns to investment considering the trade-off between higher lifetime earnings caused by additional skill formation and its costs. Table 2.8 summarizes the results. Two factors drive the decision of how long to attend university. First, gifted students will accumulate skills more easily and thus obtain a higher benefit from attending tertiary education. Second, students from more favourable environments achieve higher gains from attending university. Hence, highly gifted students from favourable environments tend to remain longest in university even though they also face the highest opportunity costs. Less gifted individuals from unfavourable environments who have accumulated less human capital and thus have lower opportunity costs will invest less in tertiary education. This is due to a smaller educational benefit, because of skill complementarity effects and the relatively higher education costs.

2.4.4 Wage Inequality and Returns to Education

Next we consider the relationship between wage inequality and the returns to education, which has been intensively researched in recent years (see for instance Acemoglu 2002). We set wage inequality equal to the actual level of three different countries while keeping the inequality of skills constant. Hence, we assume that the degree of inequality in wages is caused by differences in labour markets. In the first country wage inequality is relatively low with a 90:10 ratio of 1.89 (as in Norway); in the second country the 90:10 ratio is 3 (as in Germany); and in the third country inequality in earnings is relatively high with a 90:10 ratio of 7 (which is higher than in the United States but lower than in India).

For a 90:10 income ratio of 7, the average optimal adult life investment increases significantly when compared to the second case. The numbers in Table 2.9 illustrate the difference in human capital arising from the modelled labour market institutions given that the heterogeneity of skills is the same in each country. Table 2.10 contains the individual rates of return from the preschool impulse for all three countries. The numbers suggest that rising labour market inequality increases the returns to investment in education significantly. The incentive to invest in additional education rises if people enter the labour market with a higher skill premium.

2.5 Concluding Remarks

Our simulation-based evidence analyses how early childhood shapes human capital formation, growth and inequality. Our life-cycle model is adjusted in a way that captures human capital formation in Germany. A framework is presented that allows for an illustration of three reasons underlying the heterogeneity of skill formation and its long-run consequences. First, the learning multiplier decreases with age, a finding from neurobiology. The learning multiplier for cognitive skills in early childhood is assumed to be higher than for self-regulatory skills. The second type of (essential) heterogeneity in skill formation stems from different amounts of investments into skills provided by the family or the socioeconomic environment in general. The third type of heterogeneity results from individual differences in the ability to transform an educational investment into additional skills. For a population of seven individuals, we compare absolute and relative rates of return for an additional investment in early childhood and in primary, secondary and tertiary education respectively. The rates of return are assessed over the period of ages 18 to 65 for full-time, dependent workers in Germany.

Our findings have implications for human capital investment strategies. A reasonable strategy for fostering human capital is to supply children with impulses to enhance cognitive as well as self-regulatory skills until they reach early adolescence. Even though at an early age investments in cognitive skills seem more important than investments in self-regulatory skills, both types of investment complement each other and both are necessary. In later adolescence investments in self-regulatory skills are more profitable. Due to the cumulative nature of skill formation, returns are always higher the earlier an investment is made. If our synthetic society wants to maximize the sum of additional human capital, then scarce resources should be invested in students from an advantageous environment or with above-average learning abilities. If the goal of the society instead is maximising the relative returns to each individual and if heterogeneity is a result of social background, then limited resources for additional educational investments should rather be given to the most disadvantaged. If heterogeneity stems from individual giftedness, then investments should be directed to the most gifted individuals. After the age of 18, individual incentives to invest in education rise with wage inequality.

Furthermore, our findings suggest that differences in individual giftedness have a higher impact on inequality than differences stemming from the environment. If heterogeneity results from the individual ability to transform educational inputs into skills (and not from socioeconomic differences), then compensating policies directed to equity goals need more resources to be successful. This results from the property of self-productivity in the technology of skill formation and hints at the challenges that educational policies have to face when they are designed to reduce inequality. In future research, improved longitudinal and cross-sectional data, both experimental and non-experimental, needs to be collected to upgrade the empirical understanding of the cumulative and synergetic nature of age-dependent skill formation as well as the way families, schools and policies shape the future workforce, growth and inequality.

2.6 References for Chapter 2

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Figures

Figure 2.1: Learning multipliers (illustrated from ages 0 to 50)

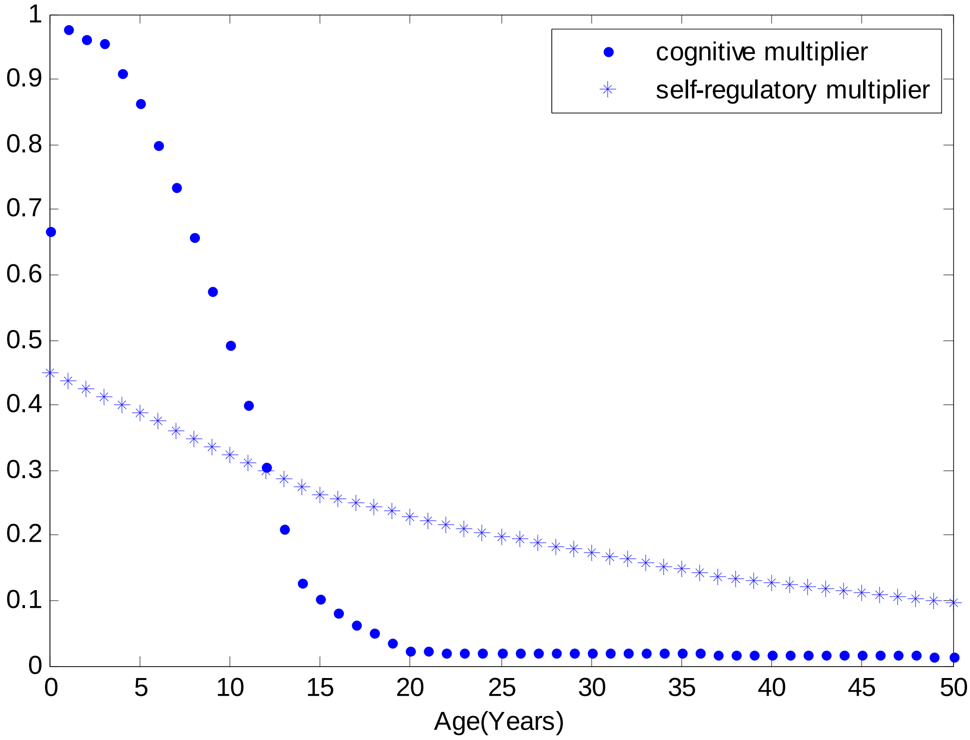


Figure 2.2: Optimised investments in skills during adulthood

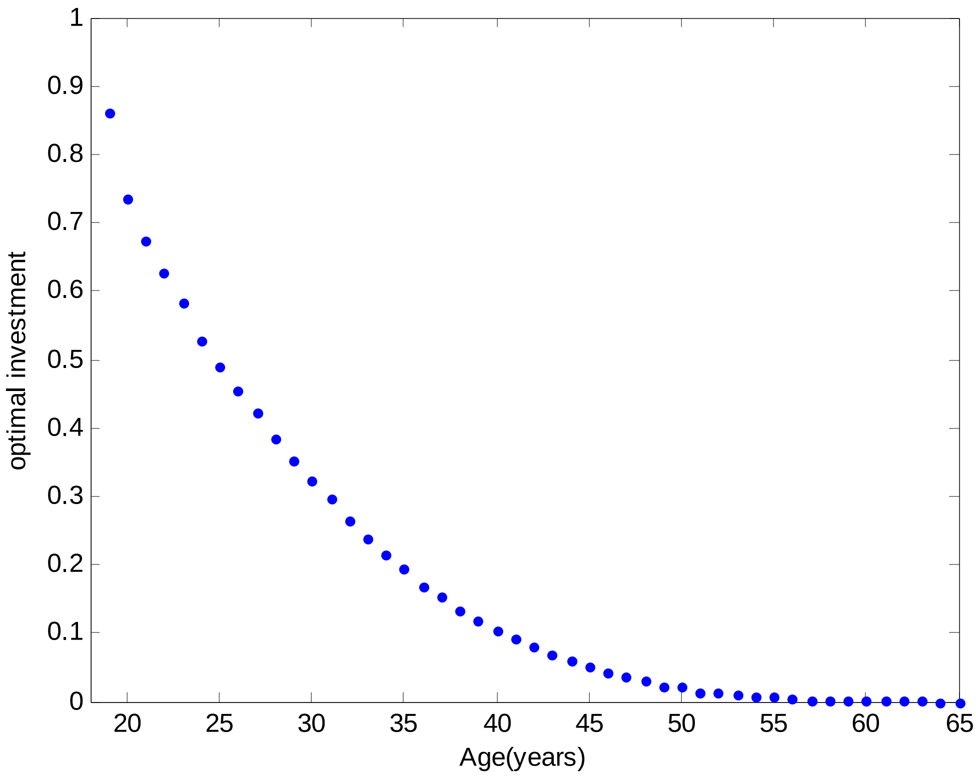


Figure 2.3: Skill development from ages 0 to 80

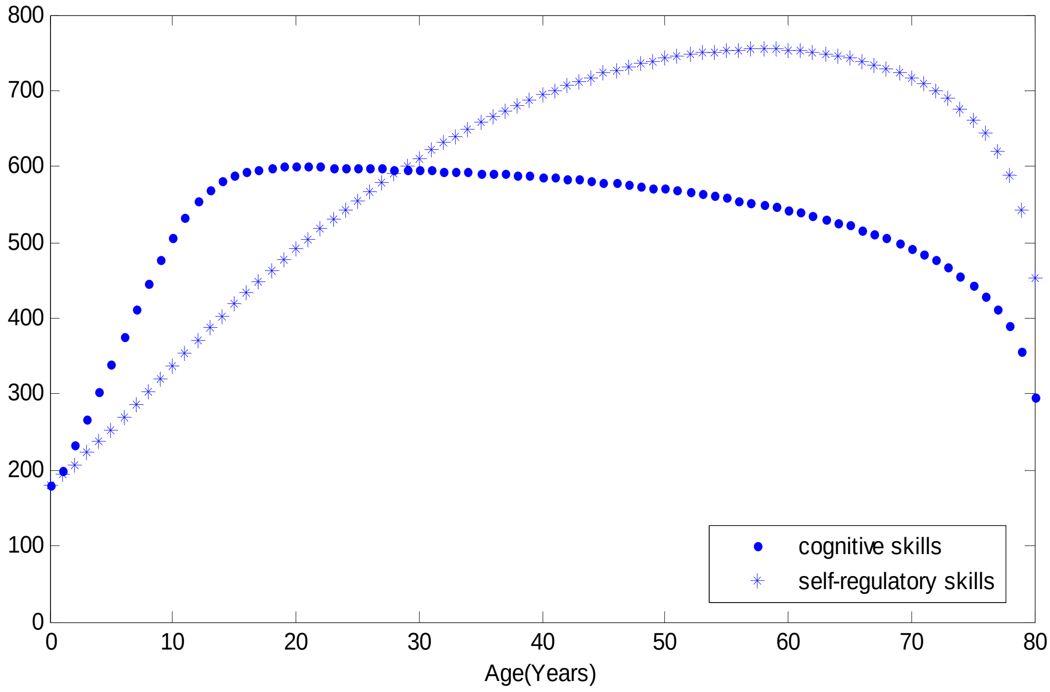


Figure 2.4: Achievement scores from ages 0 to 80

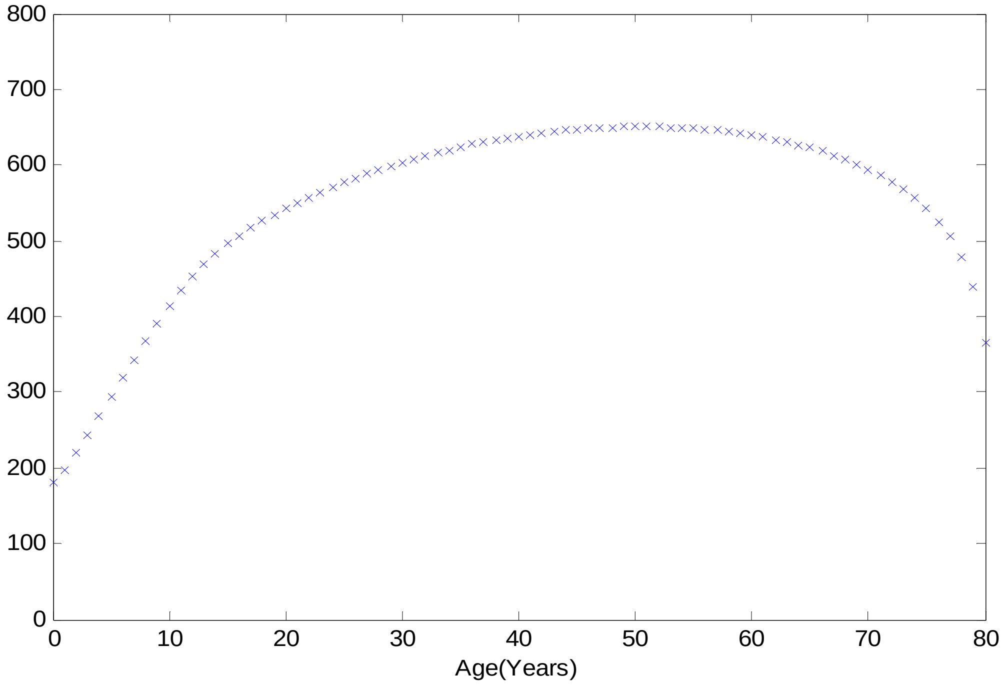


Figure 2.5: Human capital over the life cycle

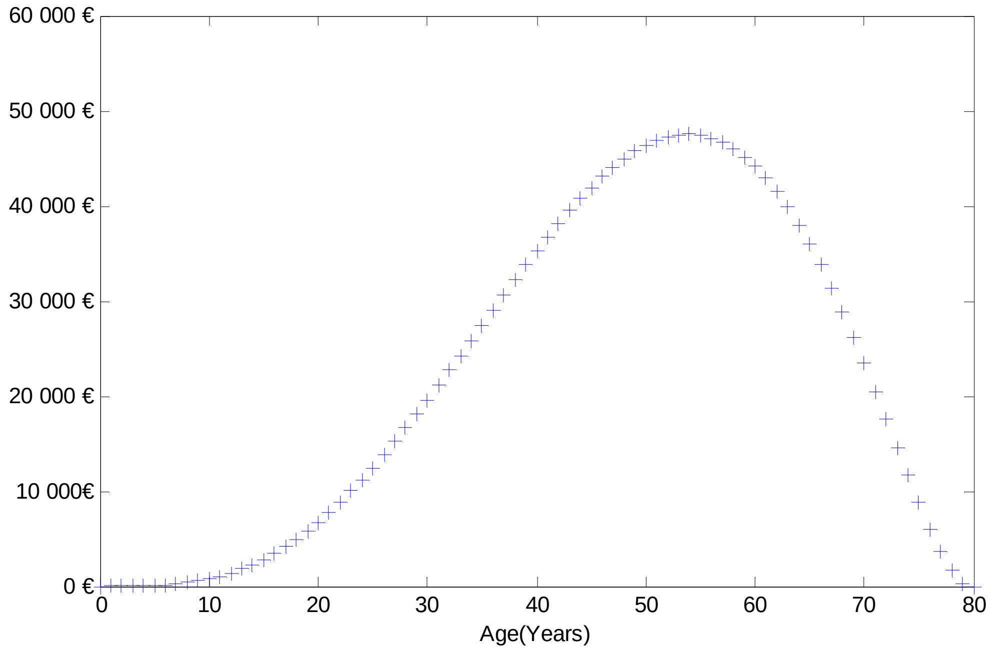
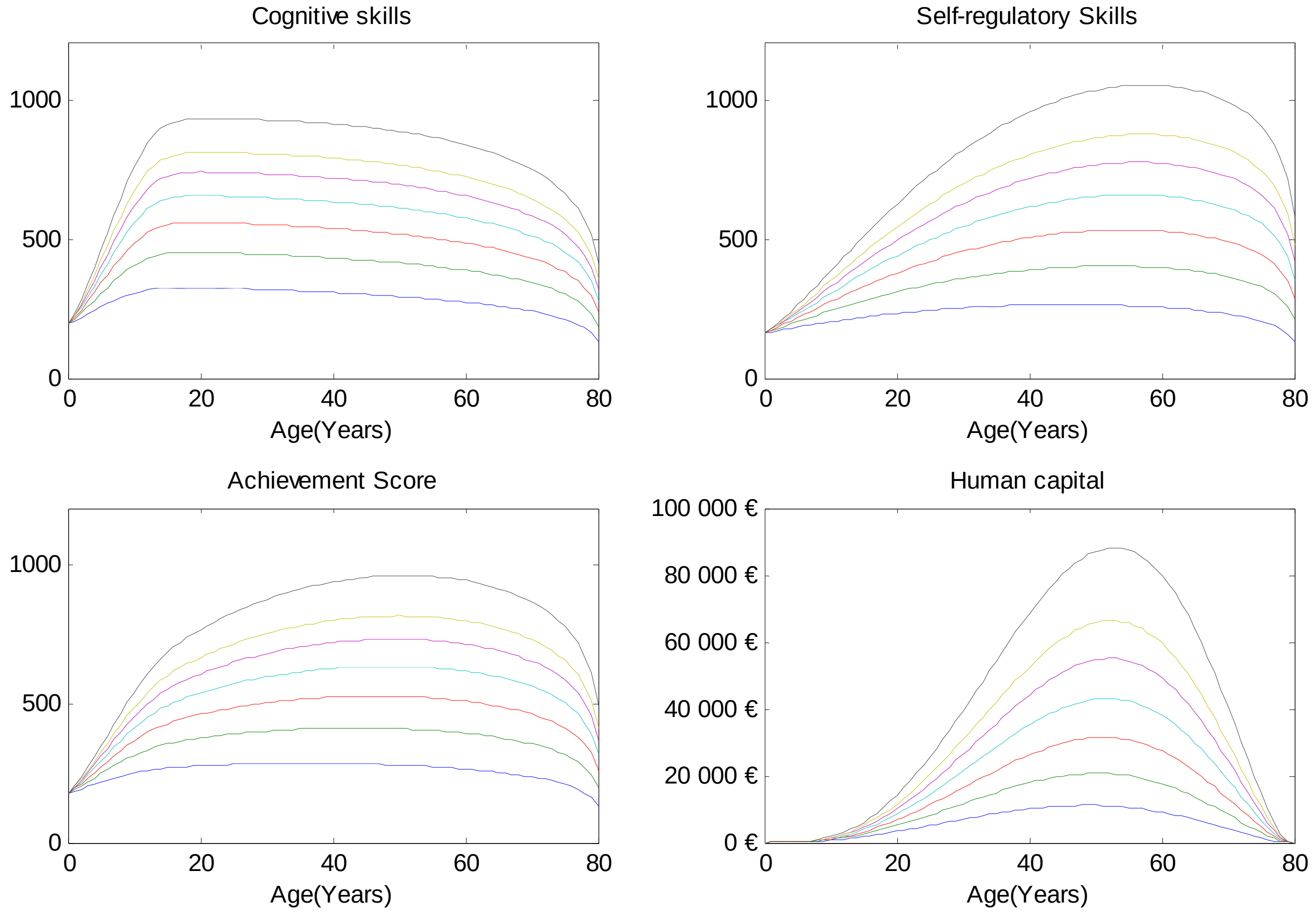


Figure 2.6: A population of seven individuals with heterogeneous environments



Tables

Table 2.1: Elasticities from Cunha and Heckman (2008**)**

	Next Period Non-cognitive	95% Confidence Bounds	Next Period Cognitive	95% Confidence Bounds
Current Noncognitive	0.8835	0.8413; 0.9256	0.0282	0.0025; 0.0539
Current Cognitive	0.0181	-0.0073; 0.0435	0.9814	0.9054; 1.0574
Current Period Investment	0.0601	0.0197; 0.1004	0.0566	0.0297; 0.0835
Mother's Education	0.0067	-0.0105; 0.0239	0.0047	-0.0075; 0.0169
Mother's Ability	-0.0063	-0.0198; 0.0072	0.0290	0.0086; 0.0494

Table 2.2: Elasticities resulting from our model (2-period mean effects of periods 8 to 13):

	Next Period Noncognitive	Next Period Cognitive
Current Noncognitive	0.92433	0.04092
Current Cognitive	0.03204	0.91775
Current Investment	0.05095	0.12317

Table 2.3: PISA reading test scores for Germany

Percentile	PISA reading score/ A_{16}
1.	236.57
10.	362.7
25.	438.95
50.	507.77
75.	568.64
90.	619.8
99.	707.23

Source: PISA 2000, OECD; own calculations.

Table 2.4: The PISA distribution for three types of essential heterogeneity

Percentile	Variation of $I_0^k \ldots I_{80}^k$	Variation of ω^k	Variation of S_0^C ; S_0^N
1.	0.01467	0.24478	57.613
10.	0.2611	0.63915	110.747
25.	0.5884	0.838	146.27
50.	1	1	180
75.	1.452	1.13238	210.945
90.	1.8929	1.23701	237.66
99.	2.7684	1.40414	284.62

Table 2.5: Returns to education in euros and relative returns for the percentiles in heterogeneous environments (discounted to period 18)

Percentile	I_0^k to I_5^k	I_6^k to I_{11}^k	I_{12}^k to I_{17}^k	I_{18}^k to I_{21}^k
1.	449,652 (27.74%)	224,646 (17.79%)	38,540 (4.29%)	-4,336 (-0.82%)
10.	618,398 (17.87%)	355,002 (11.92%)	91,729 (3.78%)	8,966 (0.60%)
25.	704,126 (14.17%)	424,170 (9.59%)	121,686 (3.23%)	15,668 (0.67%)
50.	773,887 (11.70%)	481,201 (7.99%)	146,909 (2.78%)	20,597 (0.62%)
75.	831,012 (10.00%)	528,106 (6.88%)	167,854 (2.44%)	24,065 (0.55%)
90.	876,492 (8.83%)	565,456 (6.10%)	184,584 (2.20%)	26,345 (0.49%)
99.	950,252 (7.26%)	625,836 (5.06%)	211,614 (1.85%)	29,005 (0.40%)

Table 2.6: Returns to education in euros and relative returns for the percentiles for heterogeneous giftedness (in present values at the age of 18)

Percentile	I_0^k to I_5^k	I_6^k to I_{11}^k	I_{12}^k to I_{17}^k	I_{18}^k to I_{21}^k
1.	-8,612 (-1.10%)	-17,014 (-2.23%)	-27,574 (-3.75%)	-23,681 (-4.73%)
10.	204,569 (7.65%)	118,570 (4.77%)	20,716 (0.92%)	-12,774 (-0.88%)
25.	453,737 (10.12%)	277,156 (6.73%)	76,232 (2.08%)	1,572 (0.07%)
50.	773,887 (11.70%)	481,201 (7.99%)	146,909 (2.78%)	20,597 (0.62%)
75.	1,141,632 (12.80%)	715,916 (8.86%)	227,574 (3.25%)	42,785 (0.98%)
90.	1,517,412 (13.57%)	956,106 (9.48%)	309,634 (3.56%)	65,645 (1.22%)
99.	2,312,452 (14.66%)	1,465,226 (10.36%)	482,454 (4.00%)	114,315 (1.54%)

Table 2.7: Returns to education in euros and relative returns for heterogeneous giftedness and environment, discounted to period 18

		Giftedness						
	Percentiles	1.	10.	25.	50.	75.	90.	99.
Environment	1.	192,761 (1.34%)	528,034 (8.75%)	723,242 (10.56%)	879,665 (11.60%)	1,000,000 (12.24%)	1,090,000 (12.67%)	1,220,000 (13.19%)
	10.	212,571 (1.01%)	628,308 (7.37%)	878,758 (8.84%)	1,080,000 (9.64%)	1,240,000 (10.19%)	1,360,000 (10.54%)	1,540,000 (11.04%)
	25.	224,759 (0.84%)	692,995 (6.68%)	980,378 (7.99%)	1,220,000 (8.80%)	1,400,000 (9.20%)	1,540,000 (9.51%)	1,740,000 (9.84%)
	50.	235,924 (0.70%)	754,169 (6.13%)	1,080,000 (7.37%)	1,340,000 (7.94%)	1,550,000 (8.37%)	1,710,000 (8.73%)	1,950,000 (9.13%)
	75.	245,940 (0.60%)	810,567 (5.70%)	1,170,000 (6.84%)	1,460,000 (7.37%)	1,700,000 (7.75%)	1,870,000 (8.04%)	2,130,000 (8.37%)
	90.	254,462 (0.52%)	859,642 (5.37%)	1,250,000 (6.45%)	1,570,000 (6.98%)	1,820,000 (7.24%)	2,010,000 (7.44%)	2,300,000 (7.80%)
	99.	269,261 (0.40%)	947,191 (4.87%)	1,390,000 (5.81%)	1,760,000 (6.32%)	2,050,000 (6.59%)	2,270,000 (6.83%)	2,600,000 (7.06%)

Table 2.8: Utility-maximizing duration of tertiary education in years

		Giftedness						
	Percentiles	1.	10.	25.	50.	75.	90.	99.
Environment	1.	0	0	1	2	3	4	4
	10.	0	0	2	3	4	5	5
	25.	0	1	2	4	4	5	5
	50.	0	1	3	4	5	5	6
	75.	0	1	3	4	5	5	6
	90.	0	2	3	4	5	5	6
	99.	0	2	4	5	5	6	6

Table 2.9: Discounted lifetime earnings in euros for countries differing in wage inequality

Percentile	90:10 ratio of 1.89	90:10 ratio of 3	90:10 ratio of 7
1.	351,669	173,398	48,998
10.	574,307	411,957	229,699
25.	716,921	608,674	459,777
50.	850,153	821,275	782,304
75.	971,188	1,037,480	1,183,550
90.	1,075,090	1,239,980	1,622,730
99.	1,256,930	1,630,690	2,633,750

Table 2.10: Individual rates of return for a preschool impulse with a duration of 6 years

Percentile	90:10 ratio of 1.89	90:10 ratio of 3	90:10 ratio of 7
1.	14.65%	27.59%	54.27%
10.	9.52%	17.78%	33.91%
25.	7.58%	14.13%	26.66%
50.	6.26%	11.70%	21.89%
75.	5.35%	10.02%	18.66%
90.	4.73%	8.87%	16.45%
99.	3.88%	7.32%	13.50%

3. Human Capital Investment Strategies in Europe

This part is joint work with Friedhelm Pfeiffer, published as a ZEW Discussion Paper 11-033.

Abstract

The paper analyses alternative investment policies and their consequences for the development of human capital in Europe. A model of age dependent skill formation is employed. What makes the approach special is the analysis of the returns to education of alternative educational policies targeted at certain ages, countries, or productivity levels for two counterfactual policy regimes, one regime assuming the actual state of diversity and the other a unified Europe. Our results indicate that investments need to be directed more generally to people of younger ages in Europe. If equality is important enough additional investment should specifically be directed to disadvantaged individuals during childhood. In a unified Europe, the effectiveness of policies to reduce inequality would be higher.

Keywords: Human capital investment, life cycle skill formation, welfare function, Europe

JEL-classification: D87, I12, I21, J13

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3.1 Introduction

Economists study the formation of human capital over the life cycle and its welfare consequences. According to political rhetoric educational policies overcome market failure in reaching the optimal amount of investment and in addition equalize educational opportunities. The European Commission (2010), for instance, postulates that improving the education of youth is one of the most prominent policy goals in Europe.

While most economists would agree with the aim, the optimal timing and the optimal quantity of educational investments are in question. Since deep-seated skills are created early in the human developmental process (Amor 2003, Coneus and Reuss 2010, Heckhausen and Heckhausen 2008, Heckman 2007, among others) the priorities in public educational spending are under scrutiny. The formation of cognitive skills, such as intelligence, memory power and reasoning, and self-regulatory skills, such as motivation, delay of gratification and persistence, begins in early childhood, influenced by parent-child interaction. The level of these skills is decisive for becoming a productive member of society and for economic performance as well (Cunha and Heckman 2009, Hanushek and Wössmann 2008, among others).

Although there exists a bunch of public educational programmes covering preschool, primary and secondary education in all European countries, a comprehensive empirical assessment of the patterns of investment into human capital during the life-cycle and its welfare implications under different educational regimes in Europe is still not available[3].

Our contribution to the burgeoning literature on life-span human capital formation is threefold. First, we examine welfare implications of alternative educational policies to foster human capital based on a version of our model of life cycle skill formation (Pfeiffer and Reuß 2008). Second, we extend this model in several dimensions. Life span now depends on the stream of investments in childhood as is suggested by research (Castelló-Climent and Doménech 2008, Frijters et al. 2010, among others). Also, parameters that determine income inequality and economic productivity can now be independently varied in the human capital production function. The model is calibrated for a population living in 29 European countries in the year 2006. Third, a welfare function assesses the alternative educational policies with different weights put on equality as inequality aversion among countries differs. This is made for two policy regimes: One represents the actual status of labour market diversity; the other assumes the hypothetical state of a single labour market in Europe. We analyse alternative educational investment strategies aligned to specific regions, ages and productivity levels for both regimes.

The study demonstrates that additional investment should be shifted to the young population with low investments if equality within the society is important in the welfare function. If the aim of equality is less important, additional investments need to be directed more generally to people of younger ages. The welfare effects may be greater in a unified Europe in both directions.

The paper is structured as follows. Section 3.2 introduces the data and the considered European countries. Section 3.3 discusses the model of skill and human capital formation and section 3.4 the

[3] Heckman and Jacobs (2009) investigate human capital formation from the viewpoint of skill bias and greater turbulence in labour markets in Europe. Pfeiffer and Reuß (2008) examine returns to education when skill formation is age dependent. Their empirical part focuses on Germany.

calibration of these functions with the data. Section 3.5 highlights the welfare implications of alternative educational investment strategies. Section 3.6 concludes.

3.2 Data sources and descriptive findings

In what follows Europe consists either of the following 29 countries: Austria, Belgium, Bulgaria, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden, Switzerland and United Kingdom. Alternatively, Europe is a hypothetical entity constructed from these 29 European countries. Since currently there is no such political entity and aggregate official statistics are not available, these have been created from different sources. Countries have been selected such that data on educational outcomes and investment costs, demographics, GDP and the inequality of income are available.[4] [5]

Table 3.1 displays the population size, age structure, educational expenditures, GDP and income inequality for the hypothetical Europe as well as the mean, minimum and maximum values for the individual countries. They differ significantly in many of the examined characteristics. For instance, GDP per capita varies from 8,307 € (Croatia) to 62,268 € in Luxembourg. The hypothetical European has an average GDP per capita of 22,329 €. Inequality is measured with the ratio of the highest and the lowest quintile, which varies from 3.4 (Denmark) to 7.9 (Latvia). In the hypothetical Europe it is as high as 6.

The measure of educational performance has been taken from PISA scores 2006 (OECD 2006) averaged for math, science and reading for each of the 29 countries. Table 3.2 compares the resulting average PISA scores for Europe and summarizes the mean, and the minimum and maximum values. As a rule, the inequality of educational performance is inversely related to the average PISA score. For instance, the 90-10 PISA ratio is 2 in Romania compared to 1.5 in Finland. There is a wide variety of educational expenditures per PISA score. Investment varies from 5 € (Croatia) to 25 € (Norway).

[4] GDP per capita is calculated for Euro 2006 values using PPP from OECD.stat (2009). The overall population sizes, the age structure and measures of income inequality have been taken from Eurostat (European Commission 2011).

3.3 Skill and human capital formation over the life cycle

The model of human capital formation consists of six equations, introduced in this section. Equation 3.1 and 3.2 govern skill development, equation 3.3 the formation of human capital formation from the age of zero to 18. Equation 3.4 governs the transformation of human capital into income, while equation 3.5 deals with the optimal investment into human capital from age 18 to 65. The welfare function of the society is summarized in equation 3.6.

There are two skills and two equations for skill formation, one for cognitive skills, S_t^C, and one for non-cognitive or self-regulatory skills, S_t^N (see equation 3.1, 3.2). These two difference equations specify skill formation and depreciation on an annual basis over the life span with individual *n*, living in country *j*. It is assumed that returns to education depend on age. Investment later in life is not able to enhance the skill level as much as in early childhood, even though the higher skill level may complement investment. In order to reflect age-dependent processes, two learning multipliers are added determining the person's learning aptitude, one for cognitive, $\mathrm{l}_\mathrm{t}^\mathrm{C}$, and one for self-regulatory skills, $\mathrm{l}_\mathrm{t}^\mathrm{N}$, respectively (see Pfeiffer and Reuß 2008). The learning multipliers depend on age in a way that is regarded to be consistent with neurobiological and psychological findings.

$$S_{t,n,j}^{k} = l_t^k \cdot \left\{ \frac{1}{3} \cdot S_{t-1,n,j}^{k}{}^{\theta} + \frac{1}{3} \cdot S_{t-1,n,j}^{j}{}^{\theta} + \frac{1}{3} \cdot I_{t,n,j}^{k}{}^{\theta} \right\}^{\frac{1}{\theta}} + (1-\delta_{t-1}) \cdot S_{t-1,n,j}^{k} \qquad (3.1, 3.2)$$

with $\delta_{t-1} = \dfrac{1}{as \cdot (le + 1 - t)}$, *k=C,N* and j=*C* if *k=N, j=N* if *k=C* and $S_{t,i,j}^k \geq 0$.

The first term of equations (3.1, 3.2) represents skill formation with a CES production function. Next period skills are produced by both types of skills and investment. The parameter θ determines the degree of complementarity among skills and investment and can vary from 1 (complete substitutes) to $-\infty$ (complete complements). For $\theta = 0$ the production function is of the Cobb Douglas type. The second part introduces skill losses. Depreciation of skills is modest in childhood and accelerates with increasing age, assuming a life span of *le* years. The life span depends on the amount of investment (the family environment) during childhood. *as* is a parameter introduced to govern the dynamics of deprecation. If *as* is larger than 1, skill depreciation accelerates towards the end of the life span. In the last period, the individual loses all skills (and dies). For the analyses a value *as*=5.85 is used. In that case, equations (3.1, 3.2) imply self-productivity ($\partial S_2^k / \partial S_1^k > 0$; this is true for $as > 1$) and direct complementarity ($\partial^2 S_t^k / \partial I_t^k \partial S_{t-1}^j > 0$) resulting from the CES production function as long as $\theta < 1$. A detailed discussion of the production function is given in Pfeiffer and Reuß (2008).

The formation of human capital in a given year is modelled as a function of cognitive and self-regulatory skills taking into account that human capital may accumulate or depreciate, for example, due to technological progress. Hence

$$H_{t,n,j} = \Psi_A \cdot \sqrt{S^C_{t,n,j} \cdot S^N_{t,n,j}} + (1 - \delta^H_{t-1}) \cdot H_{t-1,n,j}\,, \qquad (3.3)$$

where S^C_t and S^N_t are defined in equations (3.1, 3.2). Human capital depreciates according to $\delta^H_t = \theta_H \cdot \delta_t$, where θ_H is a parameter that may vary among individuals, jobs, industries or over time. A high value of θ_H induces an early human capital maximum (e.g., in sports); a small θ_H, a later maximum (as, for example, in science). It is assumed that this basic structure explains human capital formation in all European countries.

However, the countries differ in their skill premium and their distribution of income relative to the skill heterogeneity due to differences in the functioning of labour market and societies and technology. In one country an individual with a certain human capital level will therefore earn less than he or she would earn in another country. Besides that in some countries human capital heterogeneity is small relative to the income heterogeneity, whereas in other countries it is rather large. In the model, individual income results from the individual human capital and the cumulated income of the country as follows:

$$Y_{t,n,j} = \phi_j \cdot (1 - I^{k*}_{t,n,j}) \cdot \frac{\left(\dfrac{H_{t,n,j}}{\varnothing H_j}\right)^{\gamma_j}}{\sum\limits_{n=1}^{N_j} \left(\dfrac{H_{t,n,j}}{\varnothing H_j}\right)^{\gamma_j}} \cdot \sum_{n=1}^{N_j} H_{t,n,j} \qquad (3.4)$$

with N_j being the population of each country *j*. Two parameters are employed to model income patterns: ϕ_j reflects the transformation of human capital into income. E.g. if $\phi_j = 1$, one unit of human capital in the country will earn one Euro, for $\phi_j = 2$ two Euros.

Individual income depends on the parameter γ_j. The RHS of equation (3.4) includes the ratio of individual to average human capital. For the average individual *n*, the terms equal one for any γ_j. For individuals whose human capital differs from the mean, γ_j will either lead to an income above or below the average resulting from the stock of human capital. If $\gamma_j = 0$, all individuals in one country will earn the same amount of money irrespective of their particular skill levels. If $\gamma_j = 1$, individuals will earn exactly their level of human capital times ϕ_j. As $\lim \gamma_j \to \infty$, the person with the highest level of human capital will earn all the income generated in a country.

Until the age of 18, the investments $I^k_{1\ldots18,i,j}$ are assumed to depend on family background and teaching. Investments are calibrated to vary in such a way that they explains student performance. The is discussed in section 3.4. After the age of 18 years individuals choose the amount of investment that maximises their expected lifetime income. They can either invest $I^{k*}_{t,n,j}$ units into their skills (see equation 3.5) or earn an income at the labour market with the available level of human capital. If the available time is invested in education, no income can be earned. Individuals are assumed to maximize the following function (3.5):

$$I^{k*}_{t,n,j} = \arg\max \left(\sum_{t=18}^{65} \frac{Y_{t,n,j}(I^{C*}_{t-1,t-2,\ldots}, I^{N*}_{t-1,t-2,\ldots}) - (I^{C*}_{t,n,j} + I^{N*}_{t,n,j}) * 0.5 * C_j}{(1+r)^{t-18}} \right), \tag{3.5}$$

where r=0.02 denotes a discount factor of 2 per cent and parameter C_j represents the cost of one unit of education for country j. After the age of 65 all investments will be zero because not further income can be earned from that age on. As the number of people living in each country (N_j) is large and the individual impact is only marginal, it is assumed that individuals cannot influence the average human capital level of their country ($\varnothing H_j$) or the sum of human capital in their country ($\sum_{n=1}^{N_j} H_{t,n,j}$). Under that assumption equation (3.5) is solved and the individual amount of investment has been calculated.

To assess alternative educational policies, the following welfare function is used for our population (Sen et al. 1997):

$$W(Y) = (1 - A_\varepsilon(Y)) \cdot \sum_{i=1}^{N} y_n \text{ , with} \tag{3.6}$$

$$A_\varepsilon(Y) = 1 - \left[\frac{1}{\sum_{j=1}^{J} N_j} \sum_{n=1}^{N} \left(\frac{y_n}{\mu} \right)^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}} .$$

A_ε denotes the Atkinson index (Atkinson 1970), which illustrates trade-offs between efficiency and equality in educational policy. The index is a discrete measure of inequality for an income distribution of a population with N European citizens. The equation $y_i = \sum_{t=18}^{65} r_t \cdot Y_t$ represents the discounted individual income accumulated over the working life, factor μ denotes the average human capital of the population and ε is a parameter for different degrees of equity preferences in the society. Assuming $\varepsilon = 0$, a society does not care about equity at all. For $\varepsilon = \infty$, the index depends only on the welfare of the poorest individual within the society. The Atkinson Index is normalized between 0 and 1. If $A_\varepsilon(Y) = 0$, no inequality is measured in the distribution, while inequality is at its maximum if $A_\varepsilon(Y) = 1$.

The society is assumed to maximize function (3.6) for the life-cycle welfare of the European population. Educational policies are restricted by scarcity exogenously. In the case of $\varepsilon = 0$ the society will only maximize the sum of income without considering inequality. On the other hand, if $\lim \varepsilon \to \infty$, only the income of the poorest person in the society is relevant for governing educational policies. In social reality equity considerations may vary between $0.5 \le \varepsilon \le 1.5$ (Atkinson 1970).

3.4 Calibration of model parameters

To investigate educational policies in Europe, several model parameters have to be calibrated with existing data. In order to test the sensitivity of the analysis and to take policy regimes properly into account, some parameters have been calibrated for two different cases. In the first one, Europe consists of heterogeneous labour markets and educational costs, in the second one, a homogeneous labour market and homogenous educational costs are presumed. In a first step, the PISA-scores for all individuals i younger than 18 years in each country j have been obtained by a cubic spline interpolation (De Boor 1978). The PISA-score at age 15 (P_{15}) is assumed to result from cognitive and self-regulatory skills:

$$\mathrm{P}_{15,i,j} = \psi_{\mathrm{P}} \cdot \sqrt{\mathrm{S}^{\mathrm{C}}_{15,i,j} \cdot \mathrm{S}^{\mathrm{N}}_{15,i,j}} \,. \tag{3.7}$$

Equation (3.7) models the potential performance of an individual in performing a task as a function of her cognitive and self-regulatory skills at the age of 15 years. Both skills in the Cobb Douglas function are assumed to be equally important and may interact in complex ways (Duckworth and Seligman 2005). A person with a high (low) level of cognitive skills could produce low (high) results if her motivation is low (high). The factor ψ_A is an adjustment factor for different normalizations of performance scores and their respective distributions.

Investment levels $I^k_{0...18,i,j}$ are calculated in a way that in each country the PISA 2006 test score distributions for 29 European countries are generated by equation (3.7). Table 3.3 shows resulting values for $\theta = 0$[6]. They vary from 0.16 to 2.06 demonstrating the inequality of investments which stems from the inequalities in the family and teaching environment.

After period 18 investments are assumed to result from equation (3.5) and the heterogeneity of income for the same amount of skills from heterogeneous national labour markets. Based on the investments in young age, the parameter ϕ_j is calibrated such that all working individuals between the age of 18 and 65 years annually produce the GDP of the country (the sum of incomes in each country is equal to the total GDP). The GDP per capita results from the division of a country's GDP by the number of inhabitants. The parameter γ_j is calibrated to match the observed income inequality in Europe (see table 3.1).

Table 3.4 displays the calibrated parameters[7]. ϕ_j indicates how much larger income in a country is compared to its human capital, γ_j shows how much larger income inequality is compared to human capital inequality. The factor ϕ_j is large in high income countries like Luxembourg (9.77), Norway and Ireland, which have average levels of investments ($\varnothing I_{0...18}$ being close to 1). The value for ϕ_j is low in Poland (1.33), Croatia and Romania.

Croatia's human capital is only slightly below the average but the GDP per capita is much lower. Romania, on the other hand, has a low level of human capital leading to a low income. γ_j is high in countries with low human capital inequalities and high income inequality, which holds in particular for the Baltic countries (e.g., Latvia has the maximum value of 3.63). γ_j is small in countries with high human capital inequalities and low income inequality, for instance in Bulgaria ($\gamma_j = 1.42$).

If a single European labour market is assumed, there is only one ϕ and one γ for all countries. This results in $\phi = 3.51$ and $\gamma = 2.71$. The average value of γ is relatively high for a homogenous labour market in Europe compared to the average value in the case of a heterogeneous labour mar-

[6] For a more detailed discussion compare Pfeiffer and Reuß (2008).
[7] Note that values do not vary much between simulations for different values of θ. Hence, only the standard case $\theta = 0$ is documented in Table 3.4.

ket (γ_j=2.41). Thus, if Europe is assumed to have a homogenous labour market, higher inequality may result.

The life span depends on investments. The underlying empirical relationship is estimated by regression for the 29 countries:

$$\log(le) = \beta_0 + \beta_1 \cdot \log(GDP / capita) \tag{3.8}$$

The total population size is used as a weight. The estimated value of β_1 is 0.07 and is significant at the 99 % level, uncovering a strong relationship between educational investment (indicated by GDP per capita) and average life span in the sample of European countries. All combinations of income and life span that result from the estimation of parameter β_1 in equation (3.8) yield the function *le(I)* (see figure 3.1).

Life cycle skill formation is illustrated graphically in Figure 3.2. The figure considers all countries and demonstrates their heterogeneity. In the upper left it shows cognitive skills for a population of 100,000 representative European individuals of one age cohort for $\theta = 0$. All individuals are assumed to start with the same stock of cognitive skills, i.e. a value of 180, but receive divergent investments until the age of 18 years[8]. As can be seen in this figure, cognitive skills peak in the early 20s and then decline continuously. Individuals with fewer educational investments and a lower skill level have a shorter life span. The beginning of the decline in cognitive skill depends on the life span.

In the case of self-regulatory skills, all individuals start with the value of 180, too, but skills peak later, namely between the ages of 50 and 60 years. These skills are assumed to be more malleable throughout childhood (Caspi et al. 2005, Cunha and Heckman 2007). In the lower left part of figure 3.2, the development of human capital of a European population cohort is shown. For given human capital, the figure shows the incomes that an individual could receive if he or she worked full time between the ages of 18 and 65 years. In contrast to skills, income does not only depend on parental investments during childhood, but also on conditions stemming from the labour market and the general productivity in a country. In some countries such as Luxembourg and Norway, income is high relative to human capital, while in others, such as Poland and Romania it is low. Human Capital is produced by both cognitive and self-regulatory skills and peaks between the ages of 40 and 57 years. As individuals with higher skills live longer, they reach their maximum income

[8] For a discussion of different initial conditions see Pfeiffer and Reuß (2008).

later in life. In skill-intensive, high-income professions income peaks up to 17 years later than in low-income professions.

In the lower right part of figure 3.2 the amount of educational investments in adulthood that individuals choose to maximize their expected lifetime income is shown. Generally, individuals experience a trade-off: They have to decide to either start working or invest more in their education. In early adulthood when returns to education are high, individuals tend to invest more in their education. The amount decreases with age and becomes negligible with the time. Individuals with higher human capital and individuals living in countries with a high income inequality tend to invest more in education at young age.

3.5 Alternative Educational Policies

3.5.1 Alternative Policies and Regimes

We study the welfare consequences of three alternative educational policies for two policy regimes in Europe.

Policy one aims at reducing country heterogeneity within Europe. According to this policy, each student who is younger than 18 years and comes from a country with PISA scores below the average PISA score receives the amount of investments that is needed to reach the European average of educational investments during their first 18 years of life. This amount is greater than zero for all European countries that invest less than the mean value of educational investments in Europe. The additional investments differ significantly between countries.

Policy two aims at increasing investments at certain ages while treating students of all European countries in the same way. In all countries, individuals under the age of 18 receive an additional investment either in their preschool or their primary or secondary school. By our definition the preschool investment lasts from the age of 0 to 5 years, the primary investment from the age of 6 to 11 years and the secondary investment from the age of 12 to 17 years.

Policy three provides educational investments either to the lower, medium or highest third of the PISA achievement distribution for the first 18 years of life.

The amount of investments for policies *two* and *three* are calculated in a way that discounted accumulated costs equal those of *policy one*.

The three policies are investigated for two policy regimes. In the *first regime***,** European labour markets are assumed to be heterogeneous, hence, 29 different countries with distinct parameters ϕ_j

and γ_j are used in the model. Also, educational costs differ in each country. In the *second regime***,** there is one homogeneous European labour market with one ϕ and one γ. In the second regime educational costs are assumed to be uniform across Europe. Obviously, these two regimes are idealized policy regimes. Reality presumably meets the conditions of a market structure which somewhere in between one of the assumed regimes.

3.5.2 Heterogeneity in European Labour Markets

Policy one aims at reaching the average level of educational investments in all countries. To make such an investment, 0.19 % of the total annual European GDP (42.31 € per capita) has to be spent. For *policy two*, the investment amounts to 0.51 % (preschool), 0.57 % (primary) and 0.64 % (secondary) of the total annual European GDP (113.00 € to 144.00 € per capita annually). These differences result from discounting educational spending. Results for costs and returns are documented in Table 3.5.

The largest net income effect can be achieved with an additional preschool investment (19,127 € per capita), followed by an investment in education for all low-skilled students under 18 years (18,524 €). Supporting low-skilled individuals instead of low-skilled countries leads to higher net benefits. In the long run, the largest net income effect (GDP per capita) is about 515 € annually if all cohorts benefit from the policy. Hence, spending 113 € per capita annually would result in an increase of 515 € if no crowding out of educational investments took place. The smallest returns stem from additional investments in secondary education.

Results for inequality effects are displayed in table 3.6. The largest effect on the reduction of inequality is achieved if investments are directed to the low-skilled as intended by *policy three* (see table 3.6). If equality considerations become more important in the welfare function, supporting the low performing students is a welfare optimizing strategy. Finally, table 3.7 summarizes the welfare changes depending on the degree of inequality aversion in a society. Societies with a zero inequality aversion (ε=0) should shift more investments to younger children (*policy two*) while societies with a greater inequality aversion (ε>0) should support mainly the low performing students (*policy three*, low-skilled). *Policy one* is dominated by either the first variant of *policy two* or the first variant of *policy three*. However, *policy one* is always better compared to the second and third variant of *policy two* and *three*.

3.5.3 Homogeneous Labour Market in Europe

Although labour market policies are divergent in Europe, tendencies exist to unify these policies to a greater extent. The second policy regime of a unified Europe therefore might become more realistic in the coming decades. Results of investments and net benefits are displayed in Table 3.8.

In case of a uniform Europe the educational investment intended by *policy one* can only be financed to an extent that leads to 93.5 % of the average European investment due to the fact that education for countries with amounts below the average sum of investments becomes more expensive. For *policy two*, the investments amount to 0.51 % (preschool), 0.57 % (primary) and 0.64 % (secondary) of the total annual European GDP and are equal to the results for the regime assuming a heterogeneous labour market within Europe. For *policy three*, the annual spending complies with the expenditures of *policy one*. Investments of 0.115 educational units can be financed for each level of productivity.

In a homogeneous labour market, the effectiveness of educational investments aimed at reducing inequality increases, as shown in table 3.9 below. The human capital of the low-skilled increases out of proportion and reduces inequality. If additional investments are directed to the high-skilled students, inequality will rise to 6.36, moderately higher compared to 6.3 in regime one (see table 3.7).

Thus, alternative educational investment strategies have different welfare consequences for the two regimes, depending on the degree of inequality aversion in a society (see table 3.10). Societies with a smaller inequality aversion (ε=0) should shift more investments to younger children (*policy two*) while societies with a greater inequality aversion (ε>0) should support mainly the low performing students (*policy three*, low skilled). Policy one is dominated by either the first variant of *policy two* or the first variant of *policy three*, irrespective of the inequality aversion. Policy one is furthermore dominated by the second variant of *policy two*. However, policy one is always better compared to the third variant of *policy two* and the second and third variant of *policy three*.

3.6 Conclusion

The paper analyses alternative investment policies and their consequences for the evolution of human capital in Europe based on a model of age dependent skill formation. A model is calibrated for a population living in 29 European countries. In the study Europe is either the sum of these individual countries or it is a hypothetical entity constructed from the single countries. What makes the approach special is the analysis of the returns to education of alternative educational policies targeted at certain countries, ages or productivity levels for two counterfactual policy regimes, one regime assuming a single labour market and the other presupposing the actual state of diversity. In the model, investments for young individuals under the age of eighteen years are traced back to the family and teaching environment. In adulthood individuals optimize their amount of educational investments.

The results demonstrate that optimal investment strategies, whether they are oriented towards age, regions or skill levels, crucially depend on the weights a society puts on equality. If equality is important enough more investment in Europe are needed for disadvantaged children during childhood. If the aim of equality is less important, additional investments need to be directed more generally to people of younger ages. Furthermore, it turns out that high levels of income inequality and a high skill level increase the optimal amount of investments, especially during younger adulthood.

The findings result from the idea of age dependant skill formation with decreasing learning multipliers over time and decreasing marginal returns to investment in the skill production function. Further research is needed first for empirically assessing the skill multiplier from childhood in the different European countries with improved data. Second, additional research is needed to investigate the welfare consequences of public and private investment processes and alternative assumptions about their interdependencies.

3.7 References for Chapter 3

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Tables

Table 3.1: Population size, age distribution, educational expenditures, GPD/capita and income inequality for Europe and the 29 European countries

	Population	fraction below 18	fraction above 65	public [b] educational expenditures	GDP/capita [b]	Quintile Income Ratio
Europe	508 678 000	18.5 %	17.6 %	5 631 €	22 329 €	6.05
Mean [a]	17 540 620	19.0 %	16.6 %	5 769 €	23 168 €	4.67
Min. [a]	299 891	16.1 %	11.9 %	1 453 €	8 307 €	3.40
Max. [a]	82 437 995	24.9 %	20.8 %	12 168 €	62 268 €	7.90

Source: OECD.stat (2009), own calculations, see text. [a] These row shows the respective mean, standard deviation, minimum and maximum values from the 29 countries. [b] Euro, real values 2006.

Table 3.2: The distribution of PISA scores for Europe and the sample of 29 European countries

Percentile	5	10	25	**50**	75	90	95
Europe	332.7	367.4	426.7	**490.66**	557.9	607.5	634.9
Mean [a]	343.21	375.69	431.17	**490.87**	553.46	600.8	626.36
Min. [a]	263.2	290.9	344.5	**407.6**	462.3	511.6	538.4
Max. [a]	425.5	454.6	504	**556.5**	606.6	645.9	669.9

Source: Own calculations, see text. [a] These rows show the respective mean, standard deviation, minimum and maximum values for 29 countries.

Table 3.3: Simulated educational investments $I^{k}_{0...18,i,j}$ across the percentiles

Percentile	5	10	25	**50**	75	90	95
				$\theta = 0$			
Europe	0.16	0.27	0.51	**1**	1.37	1.8	2.06
mean	0.2	0.3	0.54	**0.98**	1.33	1.73	1.97
Std	0.09	0.11	0.15	**0.18**	0.24	0.25	0.25
Min	0.03	0.07	0.19	**0.5**	0.71	1.03	1.22
Max	0.51	0.67	0.97	**1.39**	1.79	2.17	2.41

Table 3.4: Calibrated values of labour market parameters for heterogeneous European countries

Country	ϕ_j	γ_j
Europe	3.51	2.71
mean	3.49	2.41
min	1.33	1.42
max	9.77	3.63

Table 3.5: Costs and returns for alternative investment policies in policy regime one

Policy		Duration in years	Investments	Annual average GDP per capita increase	Net income benefit per student
Policy one, region	**Europe**	18	**0.06**	**434 €**	**16 018 €**
	Mean	18	0.06	452 €	16 302 €
	Min	18	0	0 €	0 €
	Max	18	0.48	2 489 €	102 725 €
Policy two, preschool	**Europe**	6	**0.10**	**515 €**	**19 127 €**
	Mean	6	0.10	521 €	19 269 €
	Min	6	0.10	199 €	7 799 €
	Max	6	0.10	1 492 €	61 545 €
Policy two, primary school	**Europe**	6	**0.12**	**389 €**	**13 119 €**
	Mean	6	0.12	394 €	13 224 €
	Min	6	0.12	151 €	5 458 €
	Max	6	0.12	1138 €	44 055 €
Policy two, secondary school	**Europe**	6	**0.13**	**207 €**	**4 583 €**
	Mean	6	0.13	209 €	4 587 €
	Min	6	0.13	81 €	818 €
	Max	6	0.13	606 €	18 672 €
Policy three, low-skilled	**Europe**	18	**0.04**	**488 €**	**18 524 €**
	Mean	18	0.04	482 €	18 263 €
	Min	18	0.01	116 €	3 639 €
	Max	18	0.08	1 508 €	62 287 €
Policy three, medium-skilled	**Europe**	18	**0.04**	**312 €**	**9 942€**
	Mean	18	0.04	326 €	10 345 €
	Min	18	0.03	122 €	4 577 €
	Max	18	0.04	908 €	33 733 €
Policy three, high-skilled	**Europe**	18	**0.04**	**236 €**	**6 361 €**
	mean	18	0.04	240 €	6 379 €
	min	18	0.01	22 €	850 €
	max	18	0.07	596 €	20 536 €

Table 3.6: Changes in inequality for policy regime one

Policy	before policy	after policy	change
Policy one, region	6	5.31	-0.69
Policy two, preschool	6	5.53	-0.47
Policy two, primary school	6	5.65	-0.35
Policy two, secondary school	6	5.80	-0.20
Policy three, low-skilled	6	4.92	-1.08
Policy three, medium-skilled	6	5.92	-0.08
Policy three, high-skilled	6	6.30	+0.30

Table 3.7: Welfare changes in policy regime one depending on inequality aversion ε

	$\varepsilon = 0$	$\varepsilon = 0.5$	$\varepsilon = 1$	$\varepsilon = 1.5$
Policy 1	1.45%	1.92%	4.38%	10.82%
Policy 2, preschool	1.73%	2.33%	5.57%	14.35%
Policy 2, primary	1.19%	1.61%	3.83%	9.77%
Policy 2, secondary	0.41%	0.60%	1.54%	4.00%
Policy 3, low-skilled	1.67%	3.08%	10.65%	32.32%
Policy 3, medium-skilled	0.90%	0.89%	0.54%	-0.73%
Policy 3, high-skilled	0.58%	0.28%	-0.94%	-3.30%

Table 3.8: Costs and returns for alternative investment policies in policy regime two

Policy		Duration in years	Investments	Annual average GDP per capita increase	Net income benefit per student
Policy one, region	**Europe 29**	18	**0.04**	**385 €**	**13 554 €**
	mean	18	0.04	392 €	13 851 €
	min	18	0	0 €	0 €
	max	18	0.42	4 208 €	148 473 €
Policy two, preschool	**Europe 29**	6	**0.10**	**523 €**	**19 521 €**
	mean	6	0.10	521 €	19 390 €
	min	6	0.10	411 €	14 030 €
	max	6	0.10	715 €	29 136 €
Policy two, primary school	**Europe 29**	6	**0.12**	**395 €**	**13 396 €**
	mean	6	0.12	393 €	13 319 €
	min	6	0.12	311 €	9389 €
	max	6	0.12	534 €	20 155 €
Policy two, secondary school	**Europe 29**	6	**0.13**	**210 €**	**4 729 €**
	mean	6	0.13	209 €	4 687 €
	min	6	0.13	160 €	2 506 €
	max	6	0.13	284 €	8 127 €
Policy three, low-skilled	**Europe 29**	18	**0.04**	**482 €**	**18 221 €**
	mean	18	0.04	470 €	17 761 €
	min	18	0.01	111 €	3 960 €
	Max	18	0.08	1 107 €	44 075 €
Policy three, medium-skilled	**Europe 29**	18	**0.04**	**314 €**	**10 043 €**
	mean	18	0.04	322 €	10 307 €
	min	18	0.03	231 €	7 449 €
	max	18	0.04	386 €	12 309 €
Policy three, high-skilled	**Europe 29**	18	**0.04**	**243 €**	**6 680 €**
	mean	18	0.04	241 €	6 624 €
	min	18	0.01	44 €	1 295 €
	max	18	0.07	425 €	11 408 €

Table 3.9: Changes in inequality for policy regime two

Policy	before Policy	after Policy	change
Policy one, region	6	5.52	-0.48
Policy two, preschool	6	5.44	-0.56
Policy two, primary school	6	5.58	-0.42
Policy two, secondary school	6	5.77	-0.23
Policy three, low-skilled	6	4.68	-1.32
Policy three, medium-skilled	6	6.01	+0.01
Policy three, high-skilled	6	6.36	+0.36

Table 3.10: Welfare changes in regime one depending on inequality aversion ε

	$\varepsilon = 0$	$\varepsilon = 0.5$	$\varepsilon = 1$	$\varepsilon = 1.5$
Policy one, region	1.23%	1.72%	4.38%	12.59%
Policy two, preschool	1.76%	2.57%	7.06%	19.65%
Policy two, primary	1.21%	1.77%	4.81%	13.09%
Policy two, secondary	0.43%	0.66%	1.89%	5.09%
Policy three, low-skilled	1.65%	3.45%	13.58%	44.37%
Policy three, medium-skilled	0.91%	0.90%	0.39%	-1.56%
Policy three, high-skilled	0.60%	0.18%	-1.58%	-4.96%

Figure 3.1: Relationship between educational investments and life span

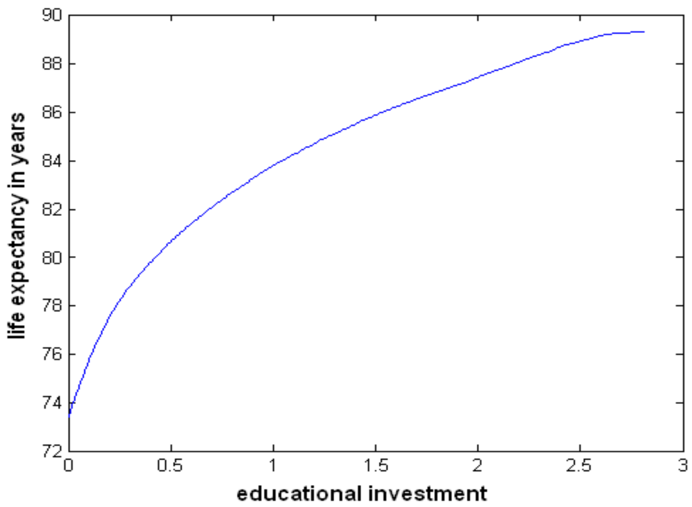
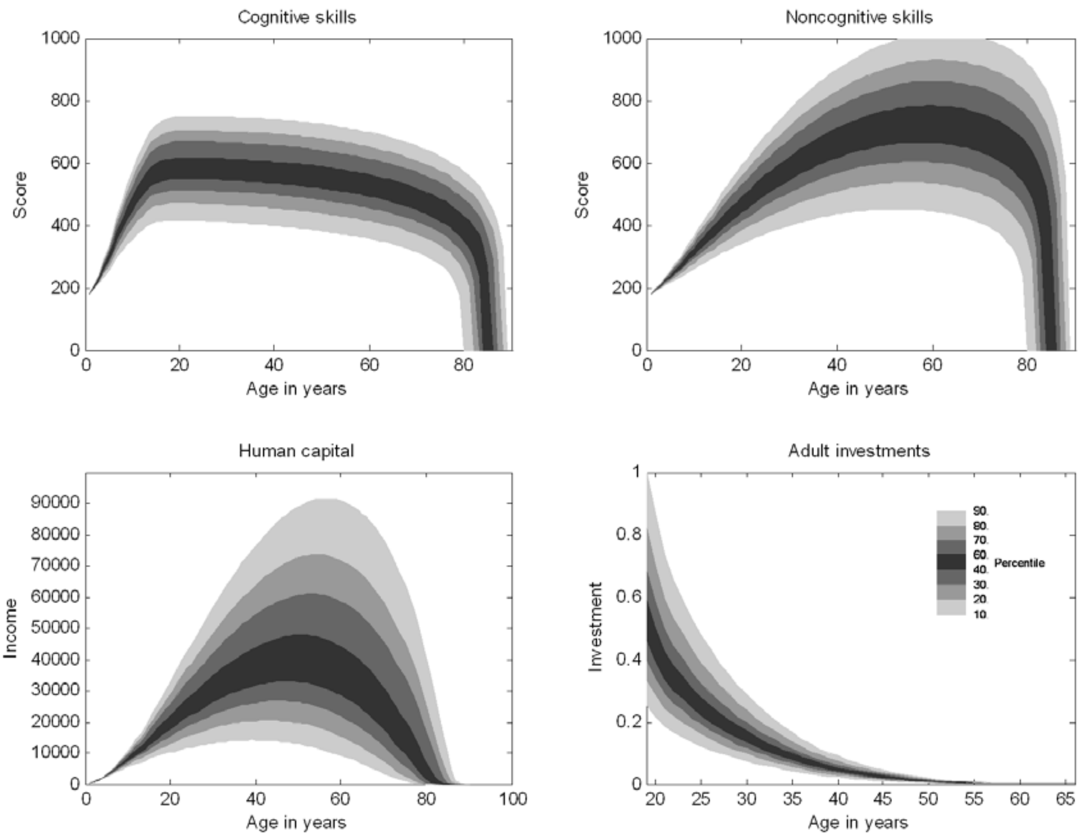


Figure 3.2: Cognitive and noncognitive skills, human capital and investments in adulthood



4. Preventative and remedial policies to reduce lifetime earnings inequality in Germany

Abstract:

The paper highlights selected aspects of intra- and intergenerational earnings inequality in the German education and federal pension system, based on human capital theory. A model of human capital accumulation across the life span is developed and calibrated taking into account inequality in skill formation and demographic trends in Germany until 2080. If policy aims at reducing lifetime earnings inequality within a generation the efficient choices are preventative investments into human capital until the age of 17 and remedial financial transfers at later ages. Due to self-productivity in human capital formation preventative policies are most effective the earlier they begin. In the intergenerational dimension additional tax financed educational investments starting in 2011 for the newborns will have beneficial effects for the cohorts born after 1976 through higher pensions. They experience an increase in their lifetime earnings, even though they finance education investments.

Keywords: pension scheme, income inequality, redistribution, demography, education, life cycle

JEL-classification: D63, H55, I20, J11

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4.1 Introduction

The paper highlights selected aspects of intra- and intergenerational earnings distribution in the German federal pension system, based on human capital theory. In Germany, inequality in public pensions is caused by earnings inequality during the working life. Earnings inequality depends on the distribution of skills. Investment in education as well as lifelong learning and occupational mobility can improve skills and competencies which affect earnings and resulting pension claims in a positive way. As wage inequality in Germany has risen since 1993/94 (see Gernandt and Pfeiffer 2007), inequality in public pensions is likely to grow for future generations of pensioners.

In this study I analyse policies to reduce lifetime earnings inequality using simulation models calibrated to inequality measure in Germany. Costs and benefits of public transfer payments (remedial policies) are analysed that directly reduce inequality with compensating investments in education at different life cycle stages, beginning in early childhood (i.e. at preschool age) (preventative policies). This is motivated by the idea that skills can be enhanced through investment in education and that skill differentials generate earnings differentials (see e.g. Cunha and Heckman 2008a, Pfeiffer 2000). In this paper the term "investment in education" is used to describe all measures being able to improve cognitive and non-cognitive skills, regardless of whether they take place in the family, by friends or at schools or other educational institutions. Both corrections of life time earnings through remedial transfers during retirement as well as preventative educational investment have their own costs and benefits for the generation of the children, the working population and the pensioners as is demonstrated.

The findings can be summarized as follows: If the policy goal is to reduce the inequality of life time earnings among people of the same generation, the results suggest preventative investment in education for people younger than 18 and remedial transfer payments for older people. Preschool-age investments lead to highest gains in lifetime earnings due to the skill multiplier during childhood. Furthermore, the results for intergenerational policies, incorporating the demographic trends in the next decades in Germany, suggest that all cohorts born after 1976 would gain from additional investments in preschool-education which are introduced in 2011 and financed through an additional income tax. The analysis shows that as a rule preventative inequality-reducing policies are cheaper than remedial ones. This insight is especially true from a life span viewpoint.

The paper is organized as follows: The section 4.2 introduces the basic simulation model of cognitive and non-cognitive skill formation and human capital accumulation. The extensions to the federal German public pension system as well as to the demographic trends in Germany are described. Section 4.3 reports the results of remedial transfer payments in comparison with preventative investments in skill formation aimed to reduce the lifetime earnings inequality within a generation (intragenerational redistribution). Section 4.4 investigates the demographic development with a focus on the pension system and discusses the findings for additional tax-financed educational investments with respect to lifetime earnings and pension payments for the cohorts of people born

1940 to 2044 over the period from 2010 to 2080 (intergenerational redistribution). Section 4.5 concludes.

4.2 A Model of Human Capital Formation over the Life Cycle in Germany

Human skills are multidimensional: Cognitive skills comprise memory power, information processing speed, intellectual power, linguistic skills as well as general problem solving abilities. However, cognitive skills alone are insufficient for devising purposes, to control actions, to manage production process tasks or lifelong learning. Skills relevant for those tasks are subsumed by the term "non-cognitive skills" in the economic literature (Heckman 2007). Persistence, self-regulation, time and risk preferences rank among these abilities (see Borghans et al. 2008, Coneus et al. 2011). Such non-cognitive skills seem to be as important with respect to human capital formation as cognitive skills are. According to Duckworth and Seligman (2005) self-discipline, for instance, seems to have a higher impact on academic success than IQ. There is intensive research on intergenerational persistence of educational and income inequality. Restuccia and Urrutia (2004), for example, find that one half of the persistence of intergenerational income inequality can be explained by the family's investment in education. In Germany, the intergenerational persistence of employee earnings is about one third (Eisenhauer and Pfeiffer 2008). According to the results of Pfeiffer and Reuß (2008a), family's investments in education can explain up to 40 percent of lifetime income inequality.

The return on human capital investments (investments in education) depend on the stage in the life cycle in which the investment was made. In particular, the early childhood seems to be a critical period for skill formation. Investments at this stage of life yield sustainable effects in human capital formation. On the one hand early investments can evolve for a longer time as skill and competency formation is a cumulative process. On the other hand, and more important, early acquired competencies facilitate further human capital formation over the life cycle. The returns on later investments through school and working life (lifelong learning) increase with the level of early investments as well as with the proceeding development of a child's skills (see Heckman 2011). This acceleration effect, modelled by a skill production function and an age-dependant skill multiplier causes preschool investments to yield higher returns over the life cycle than school investments.

Neuroscience supports childhood as a critical period of skill formation (for example, Rauh 2002). Longitudinal evidence considering children who lived in Romanian orphanages during their first years of life under very adverse conditions confirms the outstanding role of the first month of life with respect to the development of cognitive and non-cognitive skills (Becket et al. 2006). Children who were adopted in their first six months of life had an IQ being 17 points higher on average at the age of seven than children who were older than six month when adopted. These differences can hardly be caught up in later life, e.g. with normal schooling (compare Cunha et al. 2006).

In order to model these age-dependant features of skill formation, Pfeiffer and Reuß (2008a) introduce two learning multipliers determining the persons' learning aptitude, one for cognitive, l_t^C, and one for non-cognitive skills, l_t^N, respectively, see figure 4.1. The simulation model is based on the technology of skill formation by Cunha and Heckman (2007) over the whole life cycle. There are two equations, one for cognitive, S_t^C, and one for self-regulatory skills, S_t^N, that specify skill formation and depreciation for every individual over the life span on a yearly basis. The basic structure of the equation for the development of skill *k* of individual *n* in period *t* is:

$$S_{t,n}^k = \psi^k \cdot l_t^k \cdot \left\{ \frac{1}{3}(S_{t-1,n}^k)^\alpha + \frac{1}{3}(S_{t-1,n}^j)^\alpha + \frac{1}{3}\cdot(I_{t,n}^k)^\alpha \right\}^{\frac{1}{\alpha}} + (1-\delta_{t-1})\cdot S_{t-1,n}^k \qquad (4.1, 4.2)$$

with $\delta_t = \dfrac{1}{as\cdot(Le+1-t)}$ *k=C,N* and j=*C* if *k=N, j=N* if *k=C* and $S_{t,i,j}^k \geq 0$.

The first term represents skill formation as a CES production function and the second the stock of previous period's skills minus depreciation, δ_{t-1}. Next period skills are produced by the level of both skills and by investments, $I_{t,n}^k$. Thereby the learning multipliers are involved as well as ψ^k which is an adjustment factor for the units to measure skills. α is the degree of complementarity among skills and investment. Each factor in the skill production function is assumed to add to the new skills with the weight of 1/3 (the result of this assumption produces the same evidence on self-productivity provided by Cunha and Heckman 2008b)). Skill formation process is a synergetic one which is characterized by the properties of self-productivity (a high level of skills begets further competency formation) and direct complementarity (the differential return on additional investments in education increases with the stock of already acquired skills). Depreciation of skills δ_t is modest in childhood and accelerates with increasing age, life expectancy *Le* is assumed to be 80 years.

In their last period of life individuals lose all their skills (and die). Having calibrated the model that way, figure 4.2 illustrates the resulting level of cognitive and self-regulatory skills over the life cycle for the standard individual. A standard individual represents the 50th percentile of skill and income distributions and is characterized by a constant annual flow of one investment unit into the formation of skills.

Figure 4.1: Learning multipliers

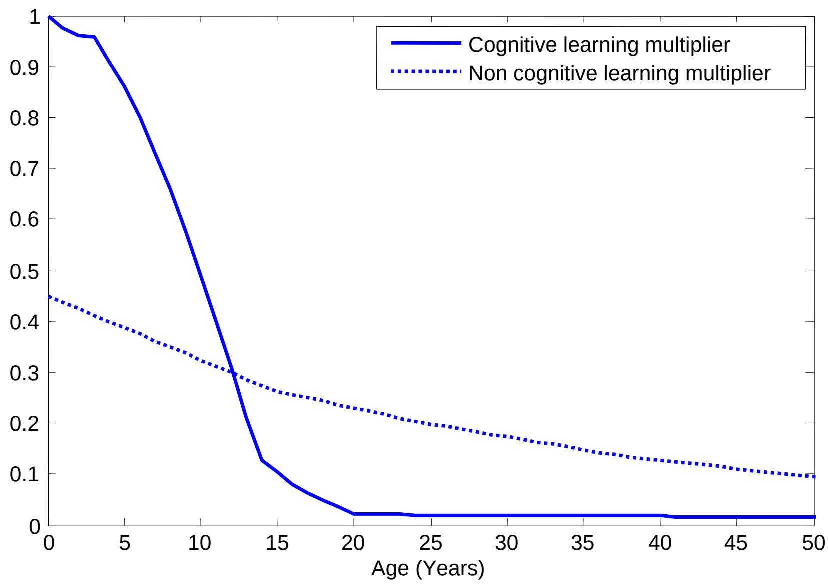
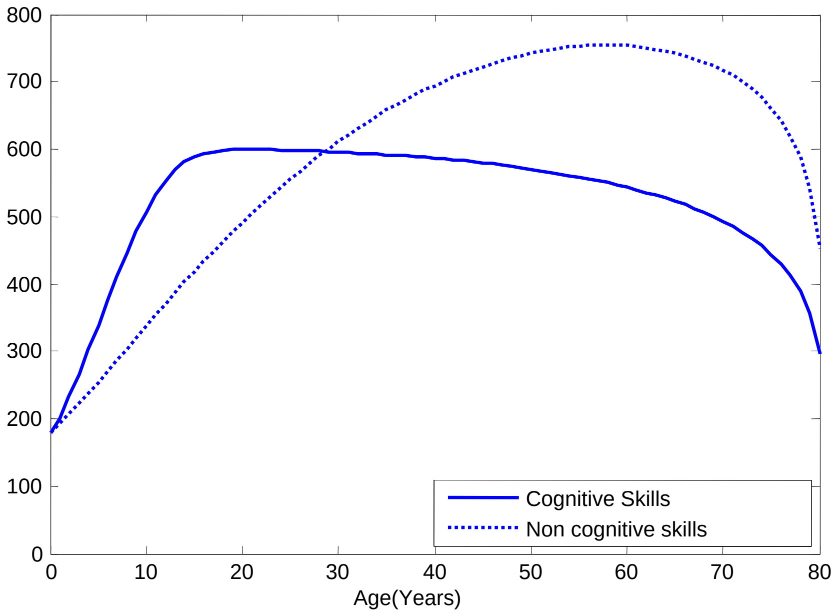


Figure 4.2: Cognitive and Non cognitive skills in the life cycle



The amount of investments is interpreted as the result of the individual's familiar and social background. Different levels of investments lead to a population of individuals whose skills will become more and more heterogeneous in the course of life. Different skill endowments at the age of birth are investigated in Pfeiffer and Reuß (2008)).

Human capital in the model is defined to be produced by the cognitive and non cognitive skills which are relevant in labour market in the sense that they generate labour earnings. Thus, the stock of human capital is a function of cognitive and non cognitive skills and is subject to depreciation:

$$H_{t,n} = \sqrt{S_{t,n}^{C} \cdot S_{t,n}^{N}} + \left(1 - \delta_{t}^{H}\right) H_{t-1,n} \tag{4.3}$$

Human capital depreciates according to $\delta_t^H = \psi_H \cdot \delta_t$, where θ_H is a parameter which may vary between individuals, jobs, industry or over time. This is similar to the loss of skills. A high value of ψ_H will lead to an early human capital maximum (like in sports), a small ψ_H to a later maximum (like in science). An age of 52 years is chosen as the human capital maximum as the human capital maximum for Germany (Franz 2009) and δ_t^H is adjusted accordingly, see figure 4.3.

Let $\theta_{t,n}$ be the fraction of working time per year. Then gross labour earnings, *GLE*, are calculated for each individual *n* from the level of human capital and the distribution of labour earnings. This distribution depends not only on the distribution of skills among the labour force but also on labour market features, e.g. on the degree of centralisation in wage negotiation or the regulation of employment. Labour markets with a more unequal wage distribution show larger earnings dispersions than human capital variation. The opposite is true for labour markets with a more uniform wage distribution.

$$GLE_{t,n} = \theta_{t,n} \cdot \psi_H \cdot \left(\frac{H_{t,n}}{H_{t,median}} \right)^{\gamma_H} \cdot H_{t,median} \tag{4.4}$$

The parameter γ_H is used to adjust the wage inequality to different labour markets. Values of γ_H larger than one strengthen the skill heterogeneity while values smaller than one reduce the earnings inequality. In Germany, the average annual gross labour earnings in the business economy are 41,468 € (Federal Statistical Office Germany 2010a). Therefore lifetime labour earnings amount to about 1.4 million € for an individual with average skills working from period 18 till 65. ψ_H is adjusted in equation (4.4) to fulfil this condition.

Subsequent to working life people get retired and receive pension payments. According to the pension formula (Deutsches Institut für Altersvorsorge 2011), the monthly amount of pension payment ("*Rentenzahlbetrag*", *RZB*, in terms of the German legislation) is calculated from the number of personal earnings points ("*Entgeltpunkten*", *EP*) acquired during working life, the access factor in pension calculation ("*Zugangsfaktor*", *Zu*), the pension type factor ("*Rentenartfaktor*", *R*) and the pension value ("*aktueller Rentenwert*", aRW):

$$RZB = EP * Zu * R * aRW \tag{4.5}$$

For simplification, it is assumed that there are only regular old-age pensions due to employment. Thus, $Zu=R=1$. The number of personal earnings points which are acquired in each year of working life are calculated from gross labour earnings of individual *n* in period *t*, $GLE_{t,n}$, the contributions assessment ceiling ("*Beitragsbemessungsgrenze",* $BBG_t = 63.929€$ [9]) and the average labour earnings according to the following formula:

$$EP_n = \sum_t^T \frac{\min\{GLE_{t,n}; BBG_t\}}{GLE_{t,average}} \tag{4.6}$$

In modelling intragenerational redistribution the pension value is determined such that it implies the average pension of 14,352 €[10] per annum in 2010 which corresponds to amount of pension payment for long-time insured persons in Germany (German Federal Pension Insurance 2011). In the case of the model dealing with intergenerational redistribution, the pension value which is given by 26.58 €[11] for 2010 is adjusted in the subsequent years according to the development of the demographic structure as well as the wage growth, which both result from the model.

4.3 Intragenerational Redistribution

4.3.1 Framework

In order to investigate on intragenerational redistribution one cohort of individuals is considered over the whole life cycle in a stationary world. Individuals differ with respect to the amount of in-

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[9] The average value for East and West Germany is calculated.
[10] The average value for East and West Germany is calculated.

vestment in their skills that they receive from their family or social environment. It is distinguished between three types of individuals: Low skilled, medium and high skilled. For simplicity, each type consists of one individual only. The low skilled person (individual $n = 1$) receives enough investment in education to exactly reach the 10^{th} percentile of the distribution of labour earnings, whereas the high skilled person (individual $n = 2$) reaches the 90^{th} percentile. The medium skilled person corresponds to the standard individual representing the median of labour earnings distribution. To simplify, the medium skilled individual is ignored when analysing intragenerational redistribution. The discussion focuses on precautionary and aftercare measures to reduce the inequality of lifetime income between the high and low skilled persons. Life expectancy, *Le*, is assumed to be fixed at 80 years in this section[12]. The model allows redistribution to have feedback effects on the investments in education during working life as individuals maximize their discounted lifetime earnings – as it is shown below.

The German Statutory Pension Insurance system (see German Federal Pension Insurance 2009) is modelled for the generation of two individuals as follows: In each period of working life the pension insurance contribution of an individual is defined by the fraction τ of one's gross labour earnings, $GLE_{t,n}$. By assumption, until retirement and during the whole phase of pension receipt two percent interests are paid on these contributions. The amount of pension payments is determined by the balanced budget condition of the pension system, i.e. aggregate pension payments, $Pension_t$, are defrayed by the sum of contributions. In this variant of the model, the level of old-age pensions is determined by the contribution rate τ during working life. τ is chosen to fit the standard individual's pension on the actual level of the average annual old-age pension for Germany (14,352 €). The balanced budget condition is given by:

$$\sum_{n=1}^{2}\sum_{t=66}^{80} Pension_{t,n} = \sum_{n=1}^{2}\sum_{t=18}^{65} \tau \cdot GLE_{t,n} \tag{4.7}$$

Individual pension receipts are based on the accumulated personal earnings points:

$$EP_{t,n} = \frac{GLE_{t,n}}{\sum_{n=1}^{2} GLE_{t,n} / 2} \tag{4.8}$$

[11] The average value for East and West Germany is calculated.
[12] Section 4.4 will introduce a more dynamic life expectancy pattern with mortality rates

The individual fraction of pension payments is calculated according to the following formula:

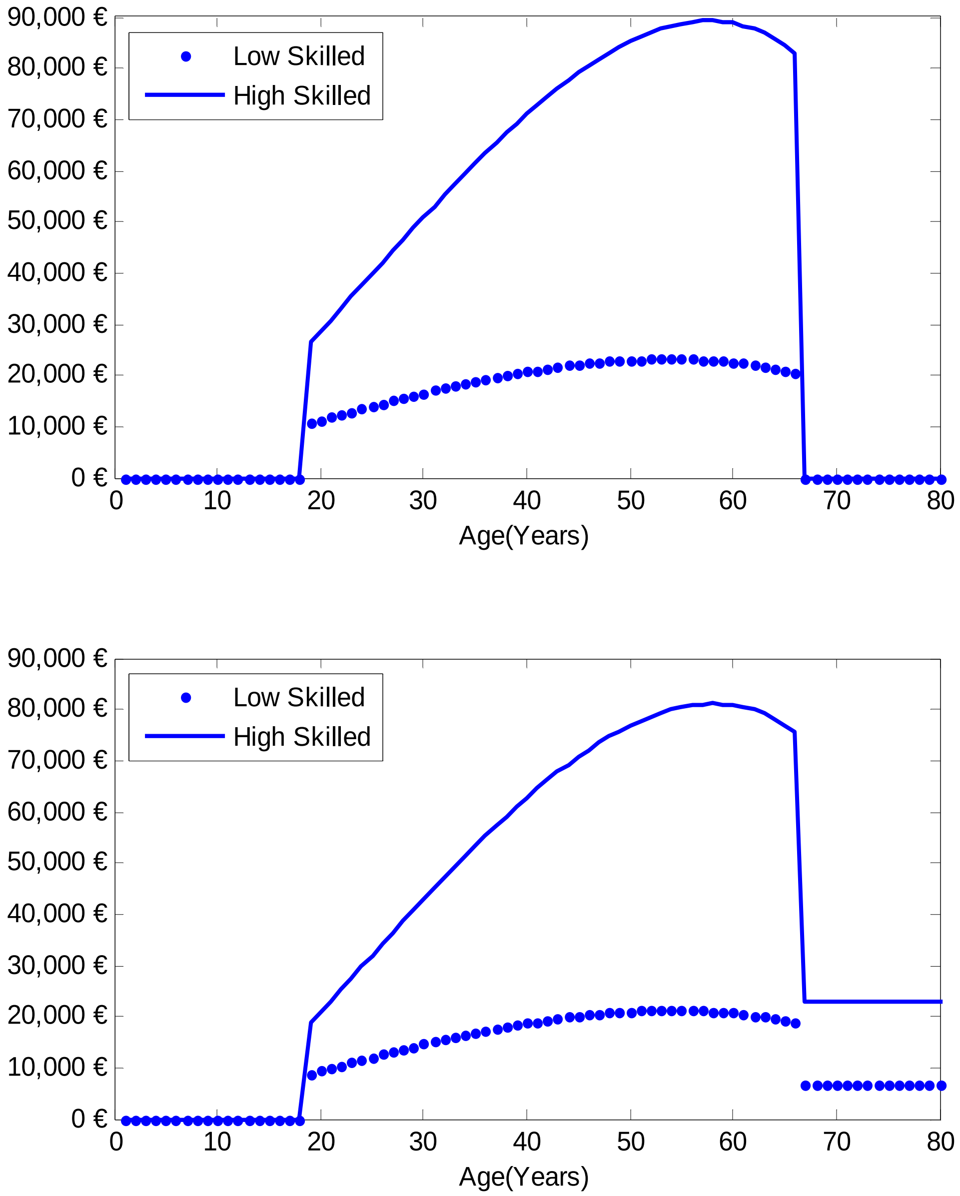
$$\upsilon_n = \left(\frac{\sum_{t=18}^{65} EP_{t,n}}{\sum_{n=1}^{2}\sum_{t=18}^{65} EP_{t,n}} \right)^{\gamma_R} / \sum_{n=1}^{2} \left(\frac{\sum_{t=18}^{65} EP_{t,n}}{\sum_{n=1}^{2}\sum_{t=18}^{65} EP_{t,n}} \right)^{\gamma_R} \tag{4.9}$$

Here $0 < \gamma_R < 1$ is a parameter that controls the (re-)distribution of pensions. If $\gamma_R = 1$, there is no redistribution and the equivalence principle is valid. For $\gamma_R = 0$ both individuals receive the same amount of pension payment which is the strongest outrage against the equivalence principle possible. For simplicity neither a social system nor a social safety net in old age is assumed. Over the life cycle the individual's net incomes are composed of net labour earnings and pensions:

$$NetInc_{n,t} = \begin{cases} (1-\tau) \cdot GLE_{n,t} & \forall 18 \le t \le 65 \\ \upsilon_n \cdot \dfrac{\sum_{n=1}^{2}\sum_{t=66}^{80} Pension_{t,n}}{15} & \forall 66 \le t \le 80 \end{cases} \tag{4.10}$$

Figure 4.3 illustrates the course of gross and net earnings for high and low skilled people over the life cycle. The inequality of earnings increases with age.

Figure 4.3: Age-dependant gross income of high and low skilled, with and without a pension system

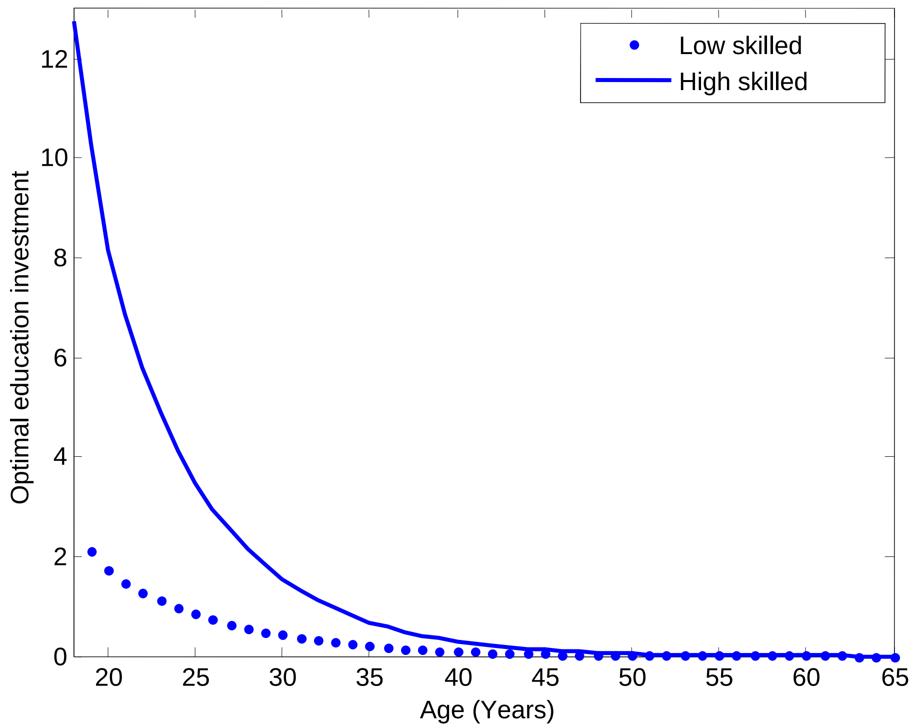


Individuals choose the amount of annual, adult investments in education, $I^*_{18...80}$, so that the sum of their discounted net income is maximized. In doing so, everybody bears the decision of the other in mind, because both investments influence each other mutually, affect the earnings of both. This interdependency follows both from wage setting and the extent of labour market inequality as well as the division of pension payments. Consequently, feedback and incentive effects of redistribution aimed to reduce inequality are taken in account by the model.

$$I_{t,n}^{C,N*} = \arg\max \left(\sum_{t=18}^{80} \frac{NetInc_{n,t}(I_{t,n}^{C,N*}, I_{t,n\neq m}^{C,N*}) - I_{t,n}^{C,N*} \cdot Cost_{t,n}}{(1+r)^{t-18}} \right) \tag{4.11}$$

Each investment unit in education of adults costs $Cost_{t,n}$ =11,478 € annually. This value equals the OECD (2010) calculation for per capita expenditures of tertiary education in Germany[13]. The optimal investment in adult life shows a steadily declining course (figure 4.4).

Figure 4.4: Optimal education investment in adult life



High skilled people invest much more than low skilled people in lifelong learning. This difference results from the cumulative nature of skill formation and demonstrates the complementarity of investments in education over the life cycle. Additional investments in education are more profitable to someone who starts working life with more skills and a higher level of human capital. Uncertainty that might have also have effects on human capital development is ignored (see Krebs 2003, Krebs et al 2010).

[13] Conversion based on the PPP (OECD.stat 2011) was conducted.

4.3.2 Measures to reduce inequality over the life cycle

In the following three possible measures to reduce the inequality of lifetime earnings between both individuals are compared. All measures have in common that there are no additional resources provided exogenously. The high skilled individuals rather have to convey some of their resources to the low skilled. This can happen at different stages of life. I consider possible costs of such transfers inasmuch as they affect the investment decisions during the working life. To measure income inequality the ratio of lifetime earnings of high skilled (90^{th} percentile) and low skilled (10^{th} percentile) is utilized. As initial condition – i.e. before redistribution is implemented – the earnings ratio is adjusted to 3.32, which is about the inequality of gross hourly wages in Germany (OECD.stat 2011, Gernandt and Pfeiffer 2007).

Various redistributions having a cumulated discounted value of 20 000 € in period 65 are computed for redistributions between two individuals, either the 60^{th} and 40^{th}, 80^{th} and 20^{th}, 90^{th} and 10^{th} or the 1^{st} and 99^{th} percentile of the income distribution. One unit of primary education is assumed to cost 6,011.92 € annually, which equals the average education expenditure in Germany (OECD 2010)[14]. The flows of resources are always discounted to the age of 65 in order to guarantee comparability. The interest rate used for discounting is set to two percent. Differing individual time preferences are ignored.

As a first measure the redistribution of pensions is examined (Pfeiffer and Reuß 2008b): In the period of pension receipt high skilled individuals have to conduct remedial transfers to low skilled in terms of financial resources. The second measure is a redistribution of preventative investments in education that are done before entering the labour force: During childhood the low skilled individual receives as much resources for investment – which the high skilled have to pay out of their resources for education – that lifetime earnings inequality is reduced to the aimed value. The third measure which is called “pension financed investment in education” analyses the effects of preventative investments in education during childhood, too. But in difference to the second measure investments in education are not taken out of the high skilled people’s educational budget, but are financed by a credit, which the high skilled have to repay during the period of pension receipt. Therefore, the model assumes a frictionless capital market that enables such transactions without costs.

The results of the comparative analysis are presented in table 4.1. It comprises average investments in education during working life, lifetime net earnings, the sum of pension payments and the total lifetime income of the analysed generation for each of the four states initial situation, redistribution of pensions, redistribution of investments in education, and pension financed investment in education.

Redistribution of pensions (see table 4.1, rows (a)) reduces the incentives for educational investment of both individuals. The reduction is larger for the high skilled person as the redistribution of pensions lowers the return on her investment in education compared with the initial situation. This means, the reduction of human capital investments leads to a decline of lifetime earnings and thus the reduction of inequality by redistribution of pensions lessens social income between -0.14 and 0 percent. For the redistribution between the 99th and the 1st percentile the loss is marginal.

In contrast, a redistribution of investments in education (see table 4.1, rows (b)) can lead to and increase or a decrease in social income depending on the percentiles. Changes in social income vary from -0.06 percent to +1.7 percent. The sum of endogenous investments in education during working life is slightly smaller if investments among types are redistributed. This leads to a decrease of social income in case of redistribution between the 60th and the 40th percentile. For distributions between the other percentiles this is not the case. The skill production function has decreasing marginal rates of return when investment is increased. Thus an equal increase is more productive for the low skill the higher the relative difference is between the high and the low skilled. Also, the additional investments in education of the low skilled induce her to invest more in her human capital during adult age. Similarly the loss of educational investments during childhood leads the high skilled to invest less during working life. As a result, a marginal redistribution of investments in education during early childhood not only reduces inequality, but also makes social income to grow if the difference between the percentiles is large enough.

In comparison, pension-financed investment in education (see table 4.1, rows (c)) does not reduce the educational attainment of the high skilled during childhood. As a consequence, her high level of skills supports the acquisition of further skills over the life cycle due to dynamic complementarity. Moreover, additional investments in education induce the low skilled person to increase her investments in human capital at adult age. The two channels combined let social income grow between 2.9 and 4.16 percent.

[14] Conversion based on the PPP (OECD.stat 2011) was conducted.

To sum up, the pension financed investment in education is the most effective measure to reduce inequality if the aim is to maximize social income. Figure 4.5 plots the social income effects of the three different measures.

Figure 4.5: Social income change of different redistribution measures

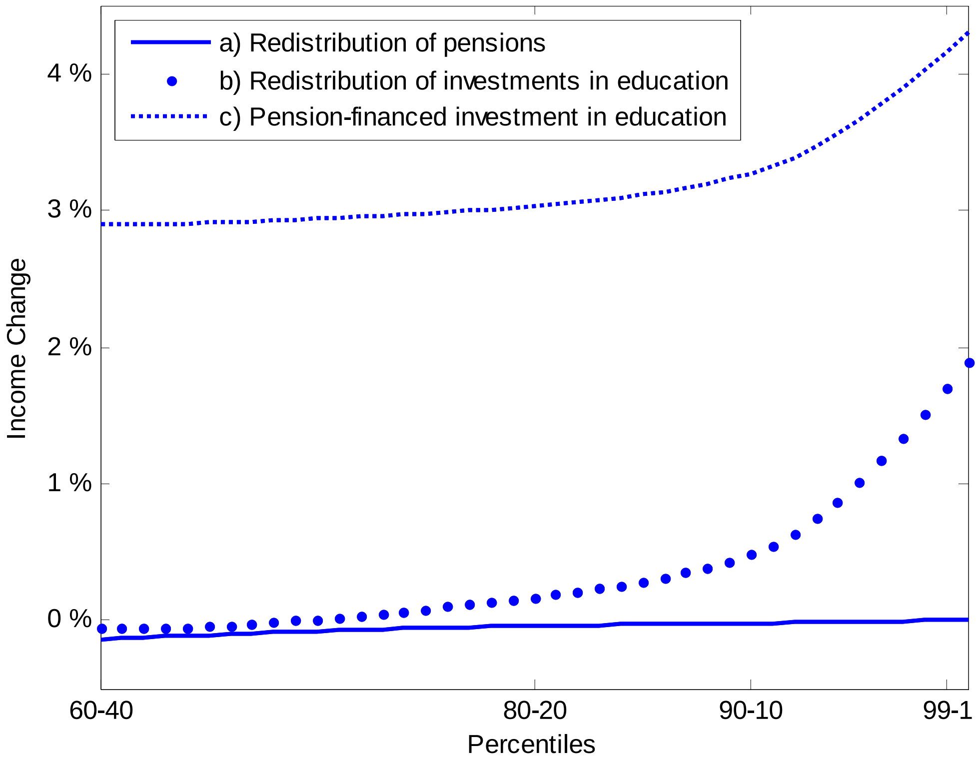


Table 4.1: Measures to reduce inequality over the life cycle for different percentiles

	investments in education during working life, Ø per annum	Net labour earnings, discounted to age 65	Cumulated pension receipts, discounted to age 65	Social income (change compared with initial situation)	Inequality Ratio
H: 60th percentile L:40th percentile					
Initial situation	L: 0.83 H: 1.13 ∑: 1.96	L: 2,466,407 € H: 3,094,008 €	L: 161,010 € H: 204,268 €	5,925,693 €	1.26
a) Redistribution of pensions	L: 0.78 H: 1.07 ∑: 1.86	L: 2,463,469 € H: 3,090,063 €	L: 180,277 € H: 183,418 €	5,917,277 € (- 0.14 %)	1.238
b) redistribution of investments in education	L: 0.9 H: 1.06 ∑: 1.95	L: 2,612,204 € H: 2,944,657 €	L: 170,933 € H: 194,057 €	5,921,850 € (- 0.06 %)	1.128
c) pension-financed investment in education	L: 0.9 H: 1.13 ∑: 2.03	L: 2,612,188 € H: 3,094,024 €	L: 170,852 € H: 220,383 €	6,097,447 € (+ 2.90 %)	1.191
H: 80th percentile L:20th percentile					
	L: 0.53 H: 1.52 ∑: 2.05	L: 1,804,949 € H: 3,833,999 €	L: 115,825 € H: 255,398 €	6,010,171 €	2.129
a) Redistribution of pensions	L: 0.53 H: 1.5 ∑: 2.03	L: 1,804,475 € H: 3,832,592 €	L: 135,647 € H: 235,130 €	6,007,844 € (- 0.04 %)	2.097
b) redistribution of investments in education	L: 0.6 H: 1.44 ∑: 2.04	L: 1,960,368 € H: 3,688,609 €	L: 126,247 € H: 245,445 €	6,020,669 € (+ 0.17 %)	1.885
c) pension-financed investment in education	L: 0.6 H: 1.52 ∑: 2.12	L: 1,960,349 € H: 3,834,027 €	L: 126,176 € H: 271,563 €	6,192,114 € (+ 3.027 %)	1.968
H: 90th percentile L:10th percentile					
Initial situation	L: 0.35 H: 1.84 ∑: 2.18	L: 1,330,668 € H: 4,401,861 €	L: 83,926 € H: 294,553 €	6,111,008 €	3.32
a) Redistribution of pensions	L: 0.35 H: 1.82 ∑: 2.17	L: 1,330,578 € H: 4,400,907 €	L: 103,859 € H: 274,371 €	6,109,716 € (- 0.021 %)	3.259
b) redistribution of investments in education	L: 0.41 H: 1.75 ∑: 2.17	L: 1,501,597 € H: 4,257,619 €	L: 95,196 € H: 284,732 €	6,139,145 € (+ 0.482 %)	2.845
c) pension-financed investment in education	L: 0.41 H: 1.84 ∑: 2.25	L: 1,501,572 € H: 4,401,906 €	L: 95,139 € H: 310,804 €	6,309,421 € (+ 3.269 %)	2.952
H: 99th percentile L:1th percentile					
Initial situation	L: 0.09 H: 2.78 ∑: 2.87	L: 539,196 € H: 5,970,516 €	L: 32,258 € H: 402,134 €	6,944,105 €	11.152
a) Redistribution of pensions	L: 0.09 H: 2.77 ∑: 2.87	L: 539,337 € H: 5,970,006 €	L: 52,243 € H: 382,063 €	6,943,649 € (+ 0.00 %)	10.737
b) redistribution of investments in education	L: 0.16 H: 2.69 ∑: 2.85	L: 795,386 € H: 5,825,731 €	L: 48,314 € H: 392,712 €	7,062,142 € (+ 1.70 %)	7.37
c) pension-financed investment in education	L: 0.16 H: 2.78 ∑: 2.94	L: 795,358 € H: 5,970,606 €	L: 48,288 € H: 418,900 €	4 685 766 € (+ 4.16 %)	7.574

4.3.3 Welfare analysis of intragenerational redistribution

Societies frequently have an inequality aversion. Thus, the total income is not always an appropriate measure to evaluate policies. An alternative measure is the social welfare function developed by Sen et al. (1997), which includes the Atkinson index (Atkinson 1970). The Atkinson Index is a discrete measure of inequality for an income distribution of a population with N individuals:

$$A_\varepsilon = 1 - \left[\frac{1}{N} \sum_{n=1}^{N} \left(\frac{NetInc_n}{\mu} \right)^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}}. \tag{4.12}$$

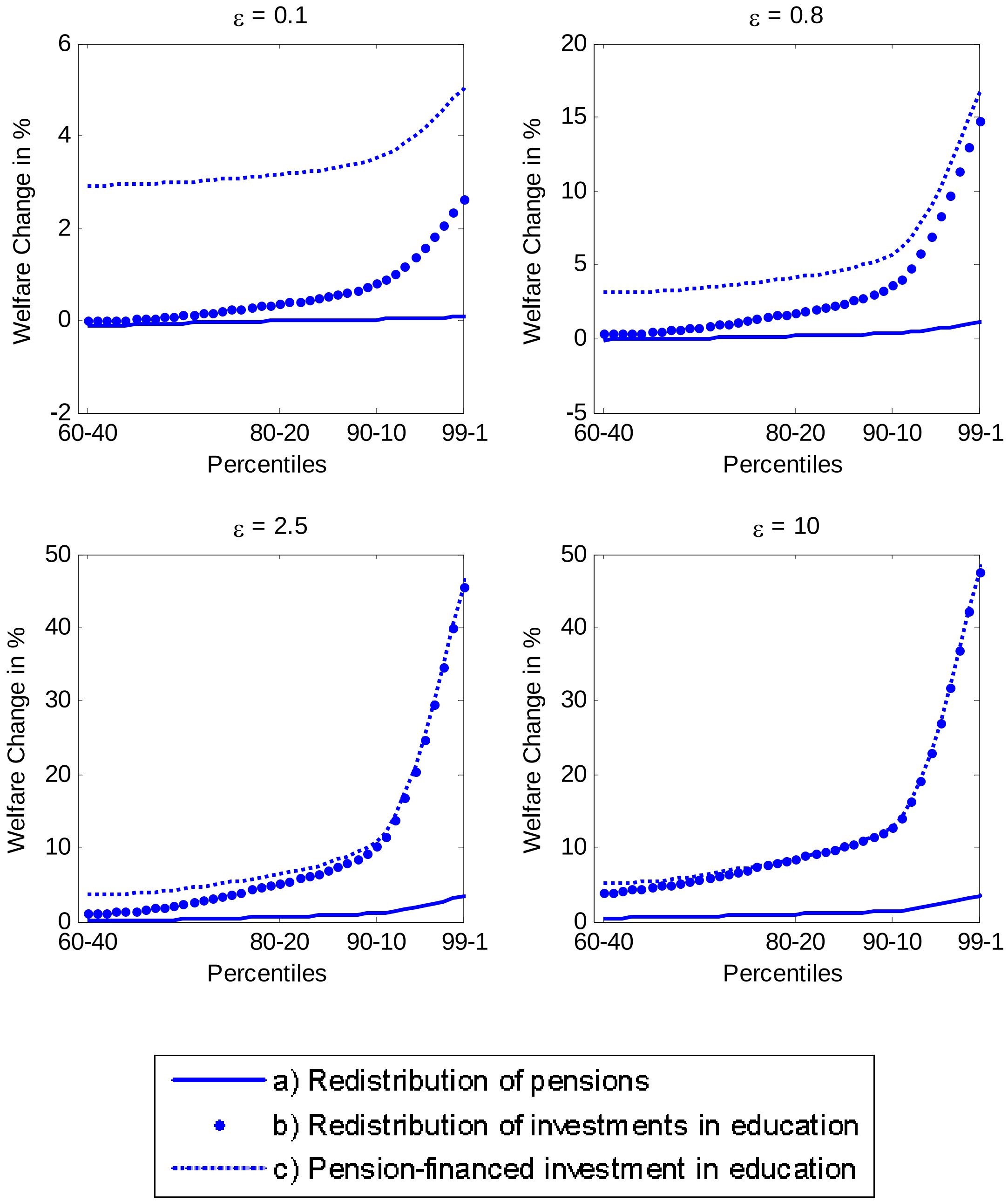
$NetInc_n$ symbols individual net income accumulated over the life span, μ the average income of the population. ε is a parameter for indicating different degrees of equity preferences in the society. For $\varepsilon = 0$ a society does not care about equity at all. For $\varepsilon = \infty$ the index depends only on the welfare of the poorest individual of the society. The Atkinson Index is normalized between 0 and 1. If $A_\varepsilon = 0$ no inequality is considered in the distribution while inequality is at its maximum if $A_\varepsilon = 1$. For empirical applications equity considerations may vary between $0.5 \le \varepsilon \le 2.5$.[15] Based on this index the following welfare function for the population can be computed (Sen et al. (1997)):

$$W(Y) = (1 - A_\varepsilon) \cdot \sum_{i=1}^{N} NetInc_n \tag{4.13}$$

Figure 4.6 shows the percentage change of Sen welfare functions from the initial situation case by policies a), b) and c). The analysis is conducted for several different inequality aversions ε = 0.1, ε = 0.8, ε = 2.5 and ε = 10. For ε = 0.1 the welfare changes are similar to the total social income changes presented in figure 4.5. For higher ε the effect of the social welfare function at the edge of the distribution is basically equal, because redistribution of investments in education (b) results in a greater inequality reduction relative to pension-financed investment in education (c) even though the gain in total social income is smaller. All in all, redistribution of investments in education (b) in no case is pareto-dominant to pension-financed investment in education (c).

[15] For a more detailed welfare evaluation of various policies see Pfeiffer and Reuß (2011).

Figure 4.6: Percentage change of Sen's social welfare function for different redistribution measures for different inequality aversion levels



The analysis suggests that the best results in reducing the inequality of lifetime earnings are achieved by an increase of preventative investments in education during childhood for low skilled individuals without reducing investments in education for the high skilled. One may object that the analysis does not exceed the framework of a manageable hypothetic world without uncertainty and therefore its validity may be limited. On the other hand, however, it can be argued that the introduction of uncertainty, e.g. with respect to the period of pension payment, would rather strengthen the above statement because the advantage of redistribution of pensions lasts only a short time of the life cycle. All in all, precautionary measures that reduce inequality tend to be cheaper than remedial corrections from an economic point of view. Moreover, precautionary measures increase social income so that the losers of redistribution, i.e. the high skilled, could theoretically be compensated.

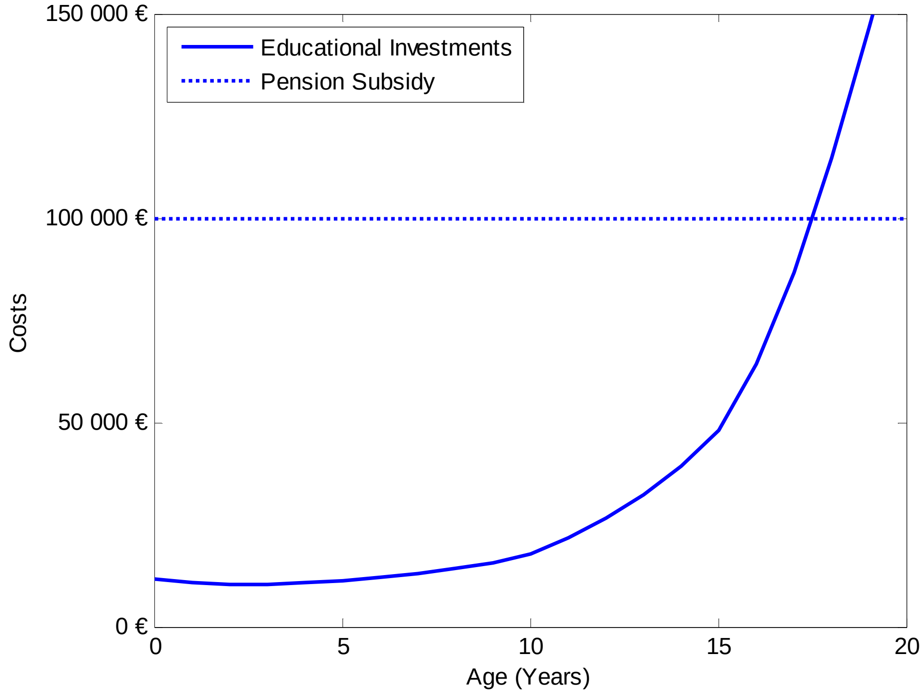
4.3.4 Age-dependant intragenerational inequality reduction

Finally the age-dependant costs for each measure that reduces lifetime inequality are analysed. As an illustration, the existence of exogenous financial resources for these redistribution measures is assumed. For reasons of comparability all values are discounted to the age of 65 years. In the case of redistribution of pensions the low skilled individual of the 10^{th} percentile has to receive 100,000 € at the age of 65 years in terms of remedial transfers in order to reduce the 90-10 lifetime earnings inequality ratio from 3.32 to 3.1.

This amount can alternatively be compared with preventative investments in education at different ages that the low skilled receives. For each stage of life, the amount of investment necessary to reach the inequality goal is determined. This results in an investment of 2,939 € in preschool age (0 - 5 years old) which corresponds to a capital value of 10,398 € at the age of 65 years - only a fraction of those 100,000 €. The main reason for this is the skill multiplier in early childhood: Early investments are especially valuable as skill formation is a cumulative process in which investments already made not only enhance future skills, but also raise the profitability of further investments. The costs increase in age as the acceleration effect becomes smaller. In the model, investment costs in education at age 17 reach the costs of the pension transfer and surmount them in later years. If additional investments in education are made afterwards, the low skilled person responds by reducing the investments during working age. As a consequence, her human capital is not affected by this redistribution measure and thus reducing inequality this way is barely possible. Besides, the investment in education necessary to reach the same effect on human capital increases in age because the depreciation of skills and human capital gradually rises (see section 4.2).

To sum up, precautionary investments in education should be preferred to redistribution of pensions through direct transfers from an economic point of view until the age of 17 years in order to reduce earnings inequality. The opposite is true for later ages.

Figure 4.7: Cost of two different measures to reduce income inequality: age-dependant compensating education investments and pension subsidies



4.4 Intergenerational redistribution

This section analyses the consequences of investments in education which are financed by an additional tax introduced in 2011 with respect to the development of public pensions in an intergenerational dimension. These additional investments in education will increase the human capital of the young generation and consequently their earnings. In the German Statutory Pension Insurance system this may indirectly lead to higher pensions even for the generation who has to finance the investment in the young because of automatic pension indexation according to wage growth. As investments in education affect productivity with considerable time lags, not all cohorts of employees will gain from the expected rise in pensions to the same extent. The simulation model is used to evaluate which generations can profit from additional, tax-financed investments in education. For simplicity, the impact of private savings on the level of lifetime earnings is ignored (for the discussion of pay-as-you-go schemes versus funded systems (see e.g. Börsch-Supan 2007, Börsch-Supan and Ludwig 2009).

4.4.1 Demographic Model

At first, the connection of the simulation of the demographic change in Germany and the skill formation model is illustrated. The foundation of the analysis is the 12th coordinated population projection by the Federal Statistical Office (2009a). The simulation covers the time span t=2010 to t=2080 and all age-groups between z=1900 and z=2080. As initial condition the composition of the population projected for the year 2010 is chosen with respect to generation and gender (Pfeiffer and Reuß 2008b). It is updated according to two differential equations, one for men $M_{t,z}$ (4.14) and one for women $W_{t,z}$ (4.15):

$$M_{t+1,z} = M_{t,z} + Immi_{t,z}^{M} - (p_{t,z}^{d,M} + p_{t,z}^{e,M}) \cdot M_{t,z} \tag{4.14}$$

$$W_{t+1,z} = W_{t,z} + Immi_{t,z}^{W} - (p_{t,z}^{d,W} + p_{t,z}^{e,W}) \cdot W_{t,z} \tag{4.15}$$

Here $Immi_{t,z}^{M,W}$ stands for immigration from abroad of people of generation z and gender M *or* W in period t. $p_{t,z}^{d,M}$, $p_{t,z}^{d,W}$, $p_{t,z}^{e,M}$ and $p_{t,z}^{e,W}$ represent the mortality rate and the probability of emigration, respectively. The mortality rates for each cohort are taken from statistics of the Federal Statistical Office (2011). Mortality rates are generally smaller for women than for men of the same age. They are likely decline in the future as a result of medical progress so that life expectancy will increase. The model is calibrated such that the life expectancy of the total population at birth will increase from 82.5 years for women and 77.3 years for men in 2009 to 86.4 years for men and 90.3 years for women in 2060. These values lie between the values of different scenarios in the 12th coordinated population projection for 2060 (89.2 years and 91.2 years for women; 85 years and 87.7 years for men). In my model the increase in lifetime expectancy occurs gradually by small decreases in the mortality rates from year to year.

The distribution of immigrants with respect to age is taken from the statistics of migration (Federal Statistical Office Germany 2009b). Immigration in 2009 amounted to 721,014 people over all age-groups while younger ages and men aged between 20 and 30 years were represented above-average. As future migration is difficult to predict, these fractions among immigrants are assumed to stay constant. About 733,796 persons emigrated from Germany in 2009. The probabilities of emigration are updated depending on age and gender – different from immigration values. Thus, as the population decreases, emigration may also decrease in total numbers.

Apart from mortality rates and migration the development of the population is mainly determined by fertility rates. According to the Federal Statistical Office Germany (2010b) in 2008 an average

German woman gave birth to 1.376 children until the age of 50 years. The model employs age-dependent fertility rates, p^g_{t-z}, of 2008 to forecast the number of newborns summed over all female cohorts:

$$Newborns_t = \sum_{z=1900}^{t} p^g_{t-z} \cdot W_{t,z} \tag{4.16}$$

With respect to gender allocation, 95 newborn girls are born per 100 newborn boys (Federal Statistical Office Germany. 2009a). As the number of births has been relatively stable for the last 20 years, varying from 1.278 in 1993 to 1.454 in 1990, they are assumed to remain constant for the simulation.

By means of these assumptions of mortality and fertility rates as well as migration the total population and its composition with respect to gender and age for each year until 2080 is calculated. With the assumptions of constant fertility rates and migration and a medium increase in life expectancy the German population will decline to about 72 million in 2050 (figure 4.8). This value lies in the middle of the spectrum (between 67 and 75 million) of the different variants in 12th coordinated population projection (Federal Statistical Office Germany 2009a). If no emigration and immigration is assumed the population until 2050 could even drop to values below 65 million.

Even if fertility rates stay constant or slightly increase, there will be a decline in the birth rate as the number of women in their childbearing years decreases. The number of annually born children will reduce from 673,000 in 2010 to 510,000 in 2050. The old-age dependency ratio[16] rises to about 52 percent due to a higher life expectancy and the retiring baby boomer generations born between 1955 and 1964. If no migration is assumed the ratio could even rise above 60 percent. The new generations that enter the labour market are smaller. Note that the rise in statutory retirement age to 67 years as decided by legislation is already recognised. Figure 4.9 shows the one-time effect of this rise in retirement age on the old-age dependency ratio. Both drops in 2012 and 2023 are caused by a rise of retirement age that is implemented in two steps only in the model for simplification. The simulation results indicate that a moderate rise in retirement age cannot stop the increase the old-age dependency ratio caused by the demographic change (similar Börsch-Supan 2007, 2011).

[16] Ratio of people above 65 years to the number of people of working age (18 to 65 years), for definition see equation 4.19

Figure 4.8: Forecasted population development, 2010 until 2050

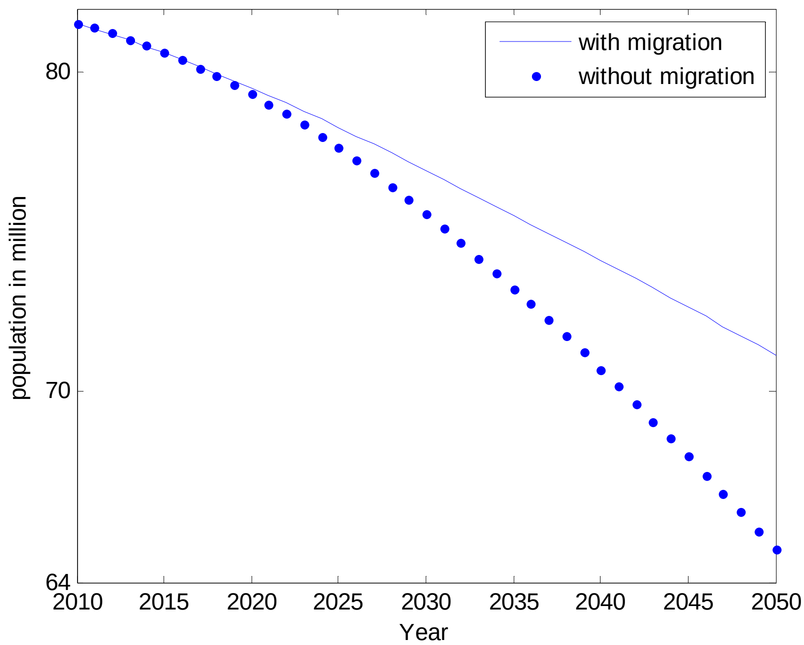
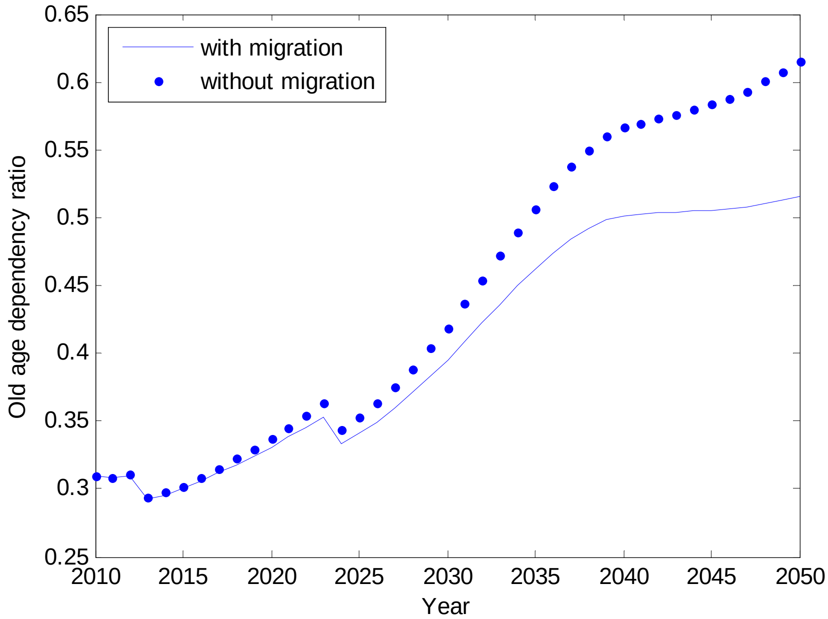


Figure 4.9: Forecast of old age dependency ratio, 2010 until 2050



4.4.2 Modelling income and the pension system

Equation 4 determines the development of gross labour earnings of 2010 over the life cycle in alternative cases of age-dependent investments in education. This equation is the basis for modelling the relationship between earnings and pension payments in the German Statutory Pension Insurance system. Calibration of γ_H and ψ_H to the average earnings and income inequality is conducted similarly as in section 4.3.1. Gross labour earnings of an employee subject to compulsory insurance, of cohort *j* and qualification group *i* in period *t* are:

$$GrossEarnings_{t,z,n} = \varphi_{Ec}^{(t-2010)} \cdot GLE_{t-z,n} \qquad \forall t - rea_t < z \leq t - 18 \tag{4.17}$$

As described in section 4.2, people earn income in the labour market from the age of 18 on, until the retirement age rea_t (at first 65, later 67 years). The parameter $\varphi_{Ec}^{(t-2010)}$ introduces exogenous economic growth which is assumed to be one percent per annum. Five differently qualified individuals in the economy represent the 10th, 30th, 50th, 70th, and 90th percentile of the earnings distribution. There are no gender differences with respect to the human capital development over the life cycle. Let θ^E be the fraction of employees in the total population which is set to 75 percent (Commission of the German government for achieving financial sustainability for the social security systems 2003). Social income obtained in one year is the sum of the individual gross labour earnings (equation 4.18) and the average employee's income average over the employed population:

$$Y_t = \sum_{z=1900}^{t} \sum_{n=1}^{5} \left(GrossEarnings_{t,z,n} \cdot \theta^E \cdot \frac{M_{t,z} + W_{t,z}}{5} \right) \tag{4.18}$$

The ratio between pension recipients and employed contributors, the old-age dependency ratio, *DR*, is given by equation 4.19:

$$DR_t = \frac{\sum_{z=1900}^{t-Rea_t} \left(M_{t,z} + W_{t,z} \right)}{\sum_{z=t-Rea_t}^{t-18} \theta^E \cdot \left(M_{t,z} + W_{t,z} \right)} \tag{4.19}$$

By means of the pension calculation formula the net social income and pension payments can be calculated (equation 4.20). They include the sum of earning points and the pension value, aRW_{2010} (see equation 4.22). For an individual *n* of cohort *z* at time *t* the monthly amount of pension payment, $RZB_{t,z,n}$, follows:

$$RZB_{t,z,n} = EP_{z,n} * Zu * R * aRW_t \tag{4.20}$$

As in section 4.3, it is assumed that there are only statutory old-age pensions due to employment (*Zu*=*R*=1). In the German pay-as-you-go system the sum of personal earnings points $EP_{z,n}$ is calculated from gross labour earnings of individual *n* in each year of working life *t*, $GrossEarnings_{t,n}$, the contributions assessment ceiling ("*Beitragsbemessungsgrenze", $BBG_t = 63.929€$*) and the average labour earnings, $\varnothing_t$, according to the following formula:

$$EP_{z,n} = \sum_{t=z+18}^{z+Rea_t} \left(\frac{\min\left\{GrossEarnings_{t,z,n}; BBG_t\right\}}{\varnothing_t} \right) \tag{4.21}$$

The pension value, aRW_{2010}, in 2010/11 in Germany is 26.58 € (German Federal Pension Insurance 2011). It is calculated according to the following formula:

$$aRW_t = aRW_{t-1} * \frac{\varnothing_{t-1}}{\varnothing_{t-2}} * \frac{100 - AVA - \tau_{t-1}}{100 - AVA - \tau_{t-2}} * \left[\left(1 - \frac{DR_{t-1}}{DR_{t-2}} \right) * \alpha + 1 \right] \tag{4.22}$$

The weighting parameter α stabilises the replacement rate for a value of 0 and the contribution rate for a value of 1 (see Börsch-Supan 2007, Krüger and Kübler 2002[17]). Its value is set to 0.25 by law (§ 68 Absatz 4 Satz 6 SGB VI) in order to avoid an increase of the contribution rate to more than 22 percent by 2030. In a pay-as-you-go system the contribution rate and pension payments depend on each other. Ceteris paribus, a higher contribution rate increases pension payments and a lower rate lowers the payments. The proportion of old-age provision factor ("Altersvorsorgeanteil") for 2010 in Germany is assumed to be 4, which is the defined value for 2012 (§ 255e SGB VI). Thus the annual, individual pension entitlement is given by:

$$Pension_{t,z,n} = aRW_t \cdot EP_{z,n} \cdot 12 \qquad \forall z \le t - rea_t \tag{4.23}$$

As a consequence, the annual total pension payments TPP_t of the German Pension insurance for the population of 5 types of individuals are:

$$TPP_t = \theta^E \cdot \sum_{z=1900}^{t-Rea_t} \sum_{n=1}^{5} \left(M_{t,z} + W_{t,z} \right) / 5 \cdot Pension_{t,z,n} \tag{4.24}$$

[17] Krüger and Kübler 2002 analyse long run equilibria between the replacement rate and the contribution rate for time-invariant preferences and demographic change across generations.

In 2010 the contribution rate to the pension insurance is 19.9 percent ($\tau_{2010} = 19{,}9$). In the simulation model the contribution rate is adjusted according to the pension entitlements on the basis of earning points:

$$\tau_t = \frac{TPP_t}{Y_t} \tag{4.25}$$

4.4.3 Measures of intergenerational redistribution

To model intergenerational redistribution from a human-capital-theoretic perspective, an earnings tax ξ is introduced, which the employees have to pay. The tax amounts to one percent of the gross earnings. The policy starts in the year 2011. The tax revenues are invested into the abilities of children in two different age-groups (0 to 6 years or alternatively, 12 to 18 years). One unit of educational investment in the model costs 6,011.92 € per year (this corresponds to the average expenditures for education in the primary school in Germany, OECD 2010). By assumption, these additional investments become effective to the full extent by the formation of skills and human capital in accordance with equation 4.1. A possible crowding out of private investments is assumed to be absent (compare Das et al. 2004). These investments will increase labour earnings in the later life. As a result the pension value the pensions of the employed persons who carry the tax will also rise in the future. The net income of individual *n* of cohort *z* at the time *t* is given as:

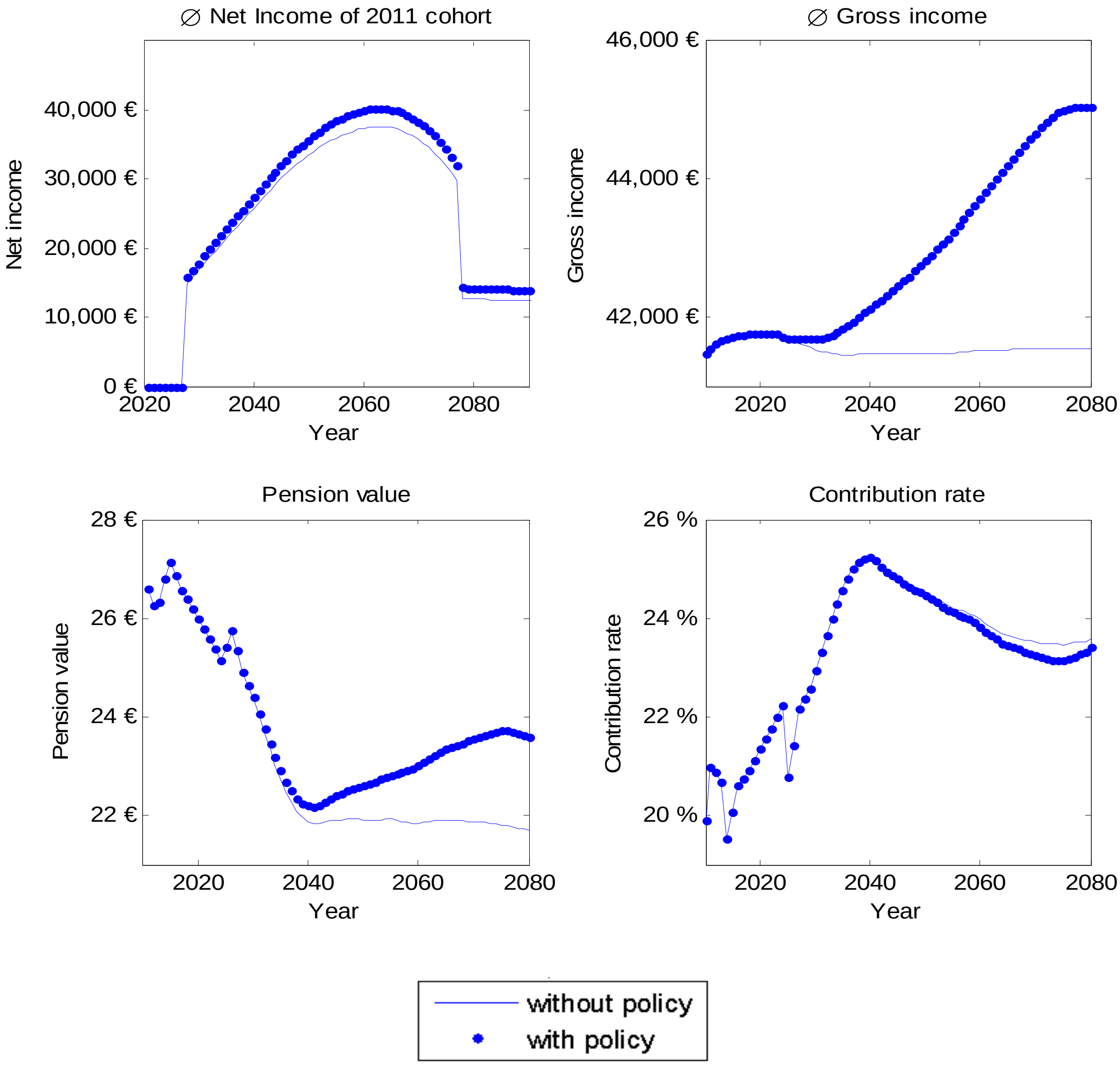
$$NetEearnings_{t,z,n} = \left(1 - \tau_t - \xi\right) \cdot GrossEarinings_{t,z,n} + Pension_{t,z,n} \tag{4.26}$$

With additional investments human capital as well as earnings of the supported age-groups will rise. For the simulation results in figure 4.10 a world without an exogenous technological progress is assumed. That way the impact of demographic change on the pension system can be isolated. Figure 4.10 (upper left) compares an individual born in 2011, who received a support for the *first six years of life* with one that received no additional support. The figure illustrates that the return on this investment in terms of a higher income takes develops with a delay of eighteen years and continues to increase with age (the gap between the two alternatives becoming greater). It peaks approximately in 2060. As a consequence of the policy, the pensions of the supported individuals at the end of life will also be higher. Figure 4.10 (upper right) shows the per capita labour earnings forecasted by the model with and without the policy. Even without the additional educational investments earnings slowly increase until the year 2025 due to the increase in the average age of employees. Subsequently a lot of baby boomers will retire causing the average labour earnings to reduce slowly. The policy however can prevent the reduction and make average labour earnings continue to rise beyond the year 2050. After 2050 the positive impacts of the human capital increase will entirely unfold.

From the year 2040 on the pension value will decrease from above 26 € to 22 €, if the pension calculation formula remains unchanged (figure 4.10, lower left). A simultaneous increase in the contribution rate will be experienced. After 2040 the pension value stabilizes on a low level. The policy impact will mainly come out only in 2040, so that the reduction of pensions cannot be stopped. From 2040 on, however, the pension value will be significantly higher than without the policy. As figure 4.10 also shows (lower right), the decrease of the contribution rate is only marginal. Due to the fact that the contribution rate increases only marginally with pensions increasing significantly, it could be possible that some cohorts have a preference for policy. This is analysed in section 4.4.4.

One could support adolescents between 12 and 17 years, alternatively. If the policy starts in 2011, benefits will already come out by 2020 in this scenario, because the older age-groups enter the labour market shortly after providing more human capital. Individuals of the 1999 cohort would then receive their support directly after the policy is implemented. The gain of the supported 1999 cohort is much smaller than if young children were supported, amounting only to an increase of 305 € of the average net income in 2050. Also, increases in the average German gross income and pension value are much more moderate (as seen in figure 4.11, upper right and lower left). This caused by the smaller learning multiplier for adolescents relative to young children (see figure 4.1). On the other hand, benefits will already come out by 2020 if adolescents were supported instead of young children, because those age-groups enter the labour market shortly after, providing more human capital than without the policy. Since this effect is only marginal (e.g. the average pension will be just 7 € than without the policy) supporting young children is generally superior. Exceptions may exist if a society wants to achieve immediate results.

Figure 4.10: Forecast of cohort net income, average gross income, pension value and the contribution rate until 2080 with and without additional early educational investments on *children younger than 6 years*



Both policies lead to positive feedback loops. In 2050, for instance, the age-groups that were supported in 2011 will have a higher amount of human capital and income, thus paying more taxes. The tax payment on the other hand is again used to support the children in the future. This effect also explains why the benefits of supporting the youngest continue to increase until 2080 compared to the benefits if adolescents are supported.

Figure 4.11: Forecast of cohort net income, average gross income, pension value and the contribution rate until 2080 with and without additional early educational investments on adolescents between 12 and 17 years

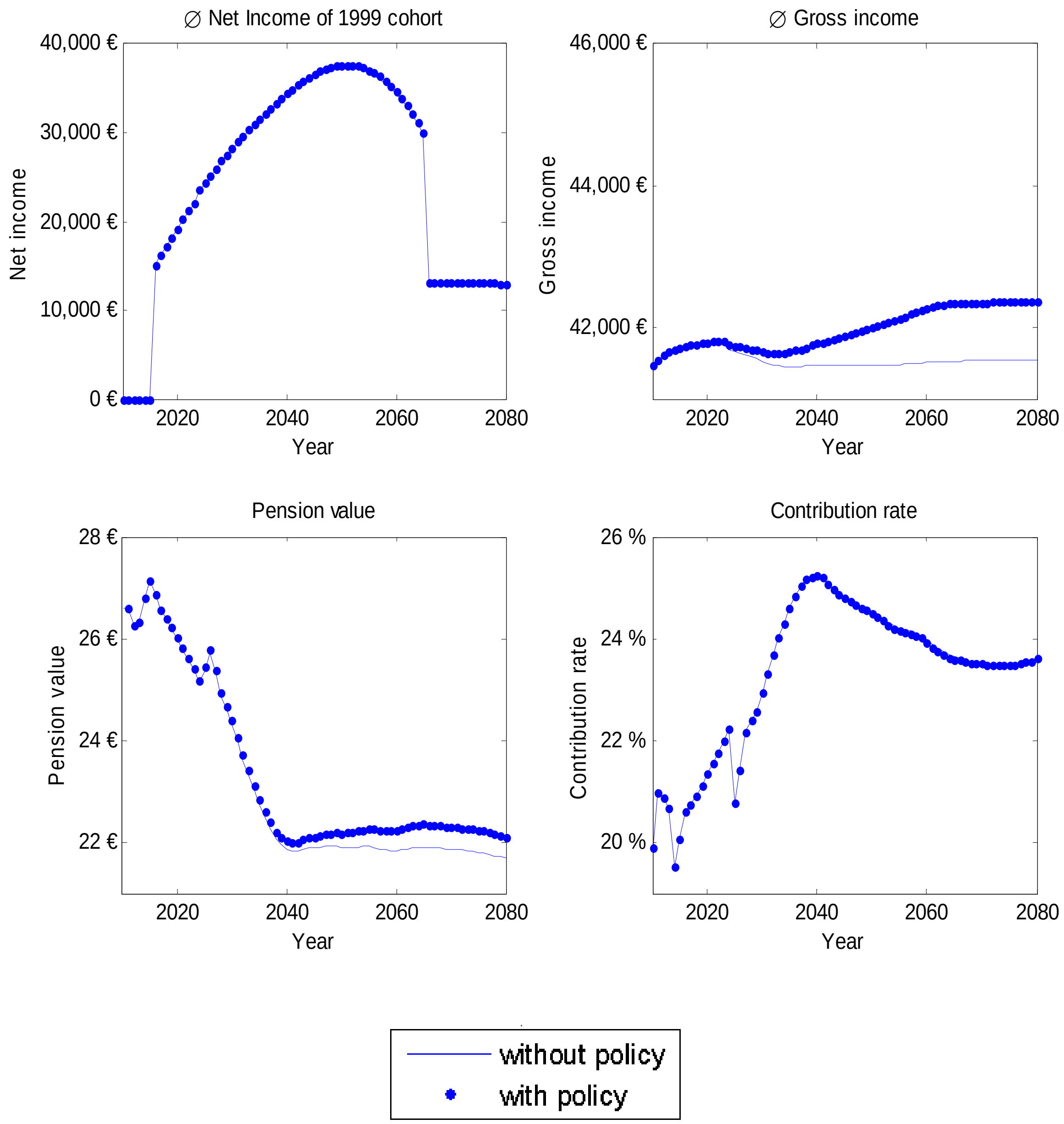
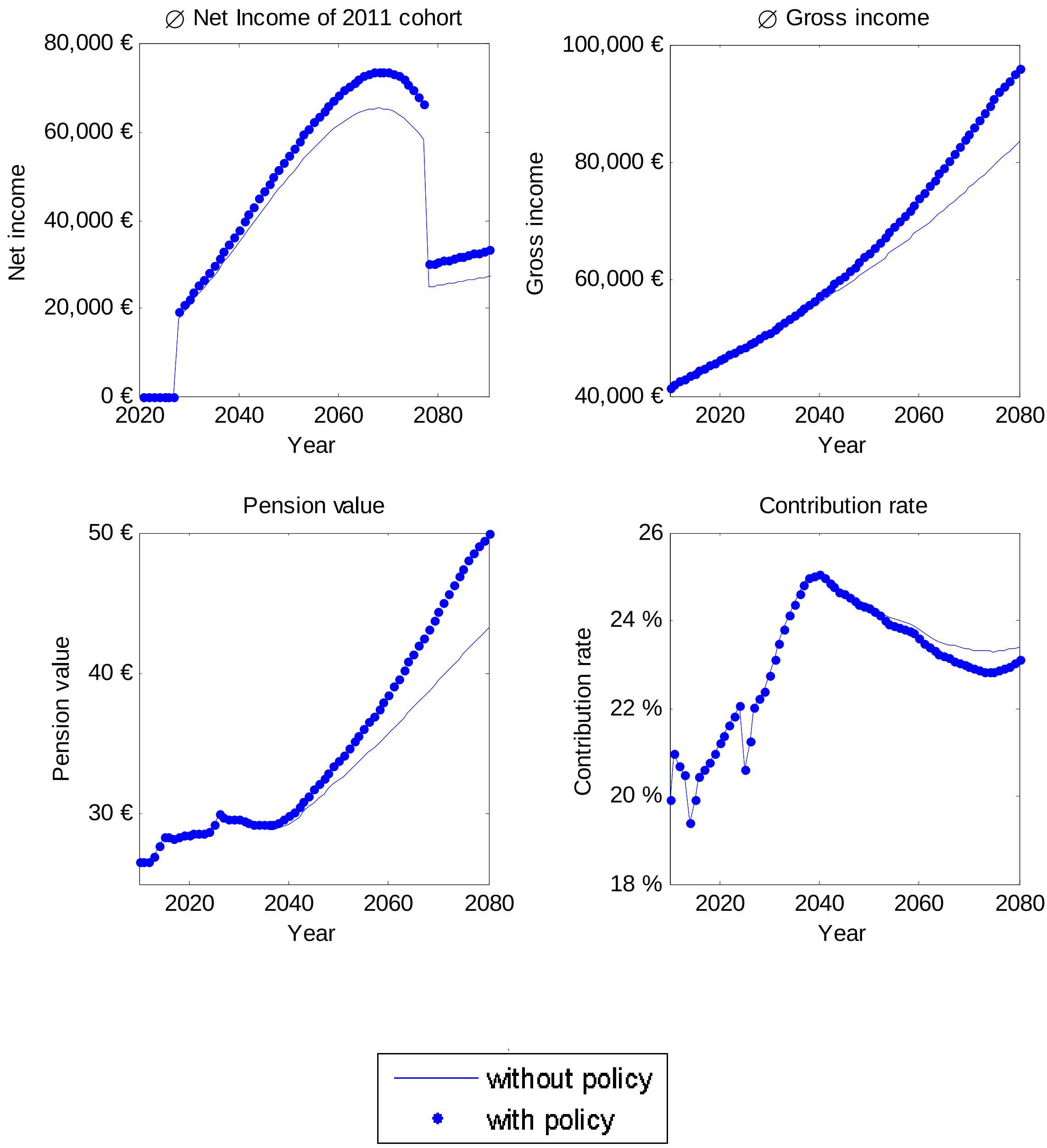


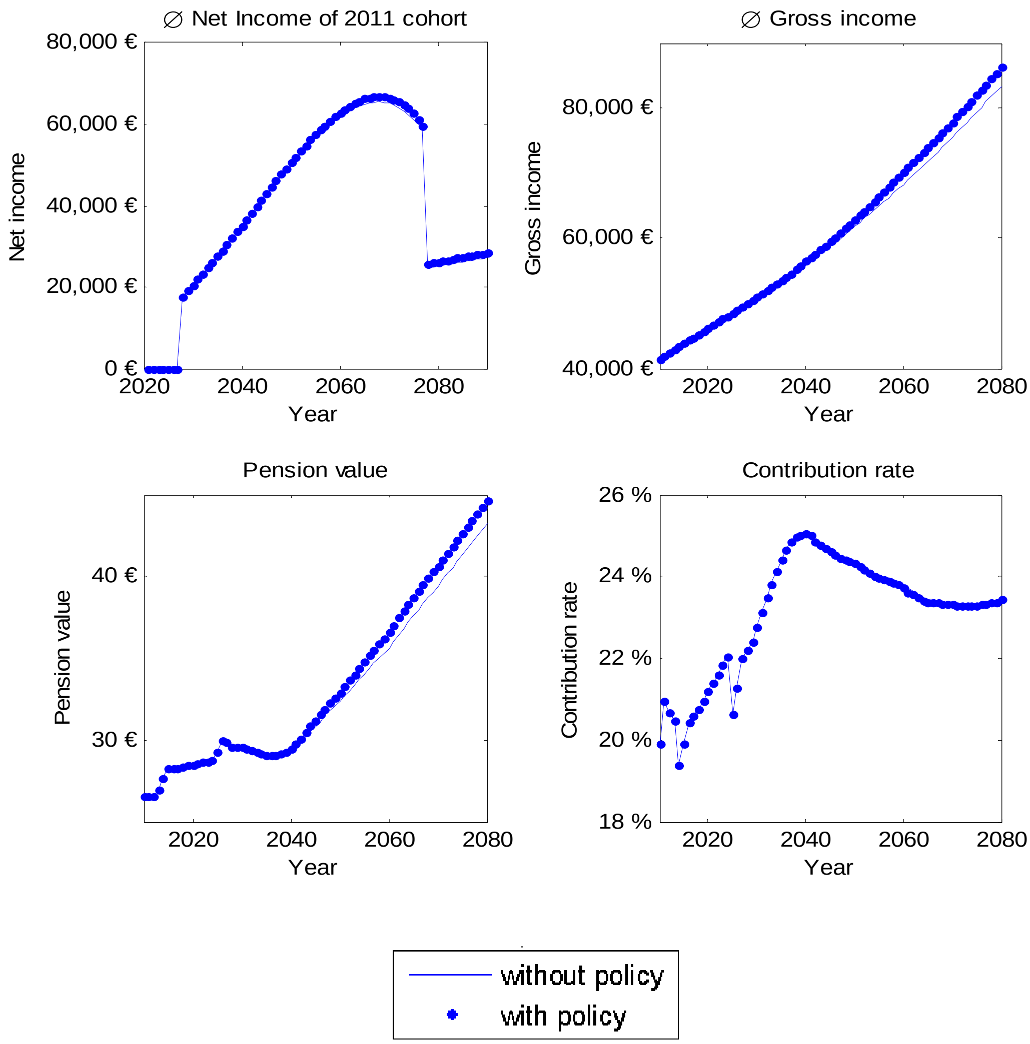
Figure 4.12: Forecast of cohort net income, average gross income, pension value and the contribution rate until 2080 with and without additional early educational investments on children younger than 6 years, with an exogenous technological progress of one percent p.a.



It is unlikely that there will be no technological progress or economic growth for the next decades. Hence, a model variant is presented that assumes an exogenous technical progress of 1 percent p.a. (compare Buchheim 1997). The parameter helps to include economic growth into the model in a very simplified way. In this case average income and pensions will not decrease as a result of demographic change (figure 4.12). Their increase will only slow down as a result of demographic changes. Despite of an annual growth in technology, for example, the average pension value however will barely rise until the year 2040. In combination with technological progress the policy benefits are greater, e.g. the policy makes the pension value rise until 2080 by about 7 € (figure

4.12, lower left) compared to approximately 2 € (figure 4.10, lower left) in the scenario with no technological progress (14 % compared to 8.4 % in relative terms, respectively). The effects on income are similar to the effect on pensions (figure 4.12, upper left, upper right). Thus human capital and technological progress in the model complement each other. The return on an investment of one Euro today is greater if the resulting human capital increase is enhanced by a better technology. As figure 4.13 shows the effects in case of a support of adolescents between 12 and 17 years are similar, but significantly smaller. This is in line with the simulation results in the scenario without any technological progress.

Figure 4.13: Forecast of cohort net income, average gross income, pension value and the contribution rate until 2080 with and without additional early educational investments on adolescents between 12 and 17 years, with an exogenous technological progress of one percent p.a.



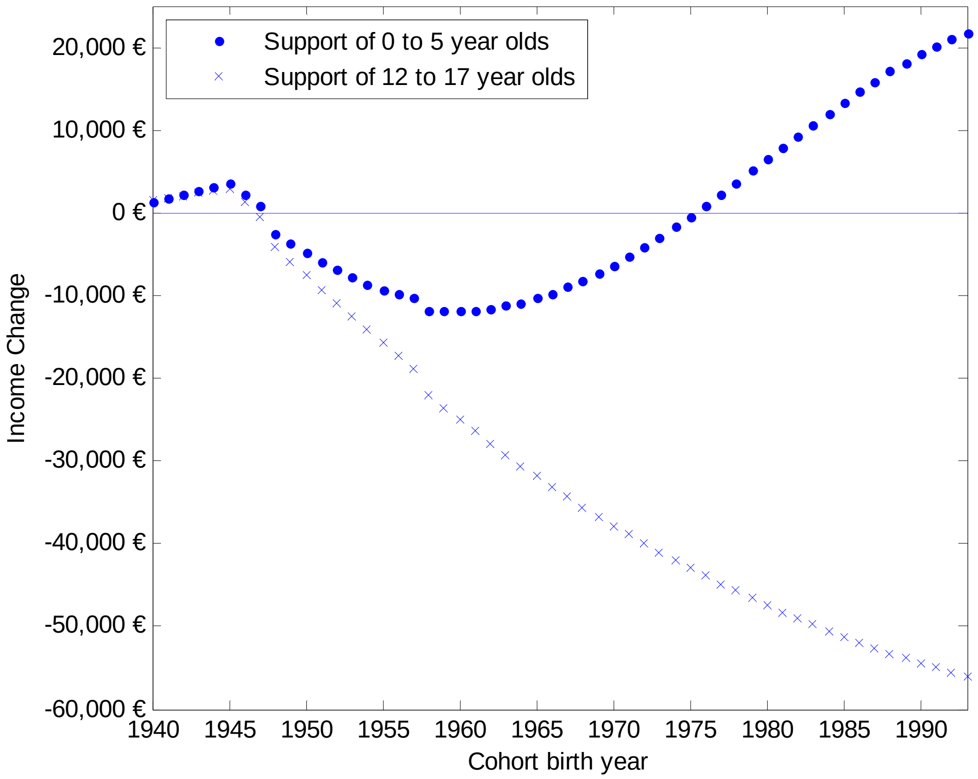
4.4.4 Lifetime income effects of different cohorts

This section investigates what employee cohorts will profit and what cohorts will lose as a result of the policy. On the one hand, individuals will have to pay a higher tax; on the other hand they can expect to receive higher pensions in old age. The first part on the section focuses on adults in the year 2010 (the employed population and the pensioners). The second part of the section will look at the benefits the supported individuals could experience in the future as a result of the additional educational support. It is assumed that time preference is the same for all individuals.

If there is no technological progress, taxes always surpass the benefit for the employees in 2010, which pay the tax. Like in the previous sections the discounted cumulated net income at the age of 65 is compared. If technological progress is one percent (see figure 4.14), age-groups born before 1945 will barely be affected by the policy, because they will neither pay additional taxes nor experience an increase in their pensions as pensions only rise with a delay of several decades. The youngest pensioners in the year 2010 have the highest expected income gain relative to the other pensioners because they still have the highest survival probability. For a significant part of the employed population, the age-groups born between 1948 and 1976, costs surpass the benefits. These groups have to pay the highest taxes while being close to their human capital peak. Higher pensions in later life cannot compensate their costs because of the strong delay and a small survival-probability until the policy benefits completely unfold. For the age-groups born between 1955 and 1965 the loss is the highest. However, employees that were born after 1976 experience an increase in life time earnings. For those groups the higher taxes are an advantageous investment, because they are still young enough to experience significantly higher pensions in old age as human capital increase accelerates as a result of additional skill investments. The pension value will then increase significantly due to the rise in wages. If technological progress is higher, also age-groups born before 1976 may benefit. If it is smaller, younger employees may have a negative utility from the policy.

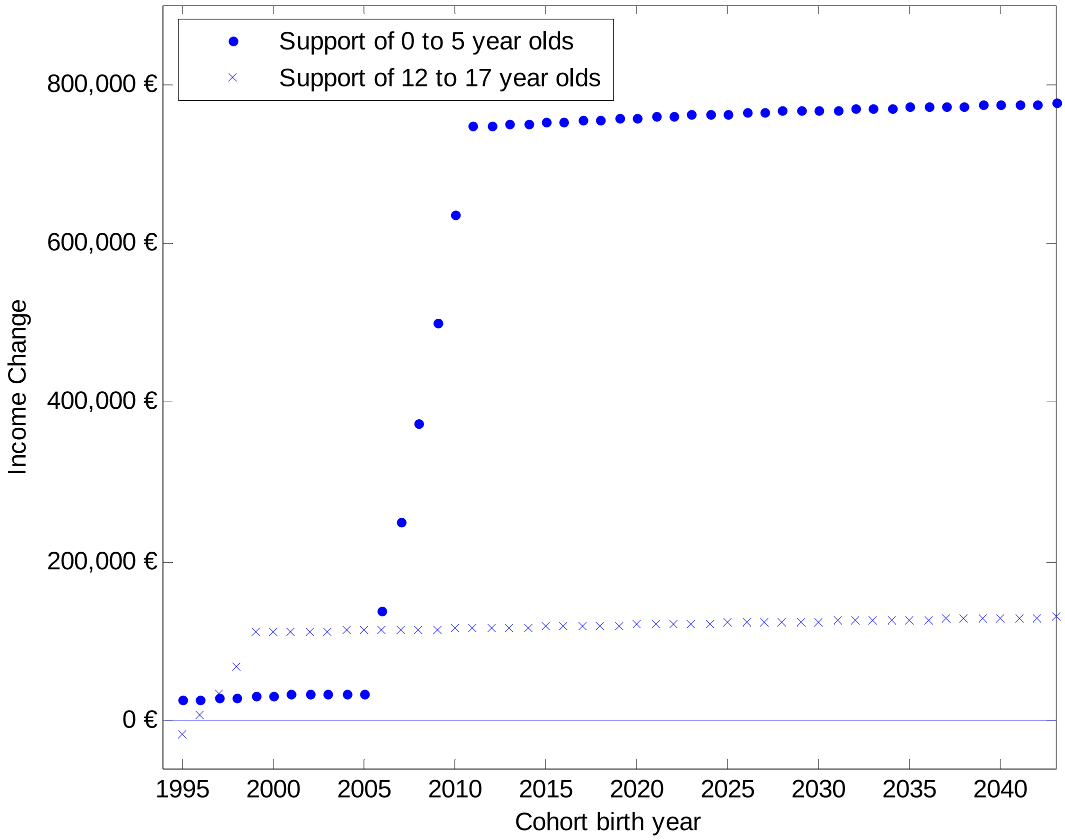
To sum up, if technological progress is sufficiently large, policy impacts are positive, but not for all age-groups. Especially age-groups that have to pay the initial taxes without receiving higher pensions in later periods might experience a negative effect on their income. If the technological progress is assumed to be one percent p.a., the baby boomers will experience losses while age-groups born after 1976 will profit. The pay-as-you-go system of the German pension system requires a long planning horizon. The longer the horizon, the more additional skills investments in early life can be recommended based on the calculations. Returns on investment into adolescents (12 to 17 years) however will always be negative for age-groups born before 1990 (see figure 4.12). The long planning perspective could however cause difficulties to politically enforce the policy in a democracy (see Kemnitz und von Weizsäcker 2003). For the age-groups born between 1994 and 2003 however supporting adolescents is superior to supporting infants, because they only profit from the investment directly if the policy starts in 2011. Thus they would vote for this alternative in the year 2010.

Figure 4.14: Change in discounted lifetime income for different age-groups by a tax-financed additional education investment in infants and in adolescents alternatively, cohorts born between 1940 and 1993



Finally, figure 4.15 shows the of discounted lifetime income for the cohorts born between 1994 and 2043. If the 0 to 5 year olds are supported, the cohort born in 2006 is the first to profit from the investments for one year as the have the age of 5 years in 2010. The cohort born in 2011 then profits from the policy to the full extent of six years. Younger age-groups experience about the same income change. If the adolescents between the ages of 12 and 17 years are supported, the age-group born in 1994 is the first to profit. The cohort born in 1999 experiences the benefits to the full extent. The gain in the discounted cumulated income is significantly smaller than to the scenario where infants are supported due to the smaller learning multiplier in adolescence (see figure 4.1).

Figure 4.15: Change in lifetime income for different age-groups by a tax financed additional education investment in infants and in adolescents alternatively, cohorts born between 1994 and 2044



4.5 Conclusions

The results of the analysis illustrate that preventative measures aimed at reducing inequality are more cost-effective from an economic point of view than remedial ones. In order to address the aspects of *intragenerational* earnings redistribution one generation in a stationary world is modelled. Individuals differ with respect to their investments in education, which they receive from the family and their social environment. The results are based on life-cycle human capital formation models. They point out that additional preschool investment in the education for the low skilled is effective. To achieve optimal results, the investment level into the high skilled during childhood however should not be reduced in the redistribution process. According to the simulation results educational investments are more effective in reducing earnings inequality than earnings transfers until the age of 17 years. After the age of 17 the relationship reverses.

In case of remedial pension transfers in old age, the "rich" pensioner would have to spend 100,000 € at the age of 65 years in order to increase the income of the "poor" pensioner so that the income inequality ratio would be reduced from 3.32 to 3.1 in Germany. To achieve the same inequality reduction of lifetime earnings the "poor" pensioner could receive additional educational investments in preschool, alternatively. If the investment can successfully be made during the first six years of life, the present value of costs (evaluated at the age of 65 years) would then only add up to 10,398 €. The reason for this result is the high skill multiplier in early childhood. Early investments are precious because skill formation is a cumulative process in which investments of the past enhance the productivity of future investments. If educational investments take place later, the present value of investment costs to reduce the inequality in lifetime earnings will surpass 100,000 € by the age of 17, thus this strategy is inferior to (remedial) earnings transfers in adult age.

In order to examine the features of *intergenerational* redistribution additional education investments starting in 2011 are evaluated in the light of the German pension system and demographic trends. The simulation results indicate decrease in the population size and a simultaneous increase of the old age dependency ratio from 30 to over 50 percent. These demographic changes are likely to cause a drop in the pension value and a simultaneous rise in the contribution rate. Technological progress could allay developments to some extent. The paper introduces tax financed educational investments as a measure to additionally ease the changes. On average benefits are positive but not for all age-groups. Especially the lifetime earnings of the baby boomers will reduce, but age-groups born after 1976 rather profit. Benefits are generally higher with a bigger technological progress. The longer the planning horizon, the more positive is the impact of educational investments on pensions in the German pension system. Investments into the youngest are the most productive. Most age-groups have an interest to educational investments, if education of infants is supported. Additional educational investments into adolescents will not cause future pensions to raise enough to compensate its costs.

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5. The Role of Parental Investments for Cognitive and Noncognitive Skill – Formation-Evidence for the First 11 Years of Life

This part is joint work with Katja Coneus and Manfred Laucht and is published in Economics and Human Biology, in press, doi:10.1016/j.ehb.2011.01.003.

Abstract:

This paper examines the impact of parental investments on the development of cognitive, mental and emotional skills during childhood using data from a longitudinal study, the Mannheim Study of Children at Risk, starting at birth. Our work offers three important innovations. First, we use reliable measures of the child's cognitive, mental and emotional skills as well as accurate measures of parental investments. The observed investments include parental health behaviour, playing and talking with the child, play materials, interests and others. Second, we estimate latent factor models to account for unobserved characteristics of children. Third, we examine the skill development for girls and boys separately, as well as for children who were born with either organic or psychosocial risk. We find a decreasing impact of parental investments on cognitive and mental skills over time, while emotional skills seem to be unaffected by parental investments in childhood. Thus, inequality at birth persists during childhood. Since families are the main sources of education during the first years of life, our results have important implications for the quality of the parent-child relationship. Improving maternal health during pregnancy and parental investments in infancy can yield large benefits for cognitive and mental development later in childhood.

Keywords: cognitive skills, noncognitive skills, critical and sensitive periods, initial risk

JEL-classification: I12, I21, J13

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5.1 Introduction

Recent interdisciplinary evidence has shown that early years are a crucial period for the development of human capital over the whole life cycle, but there is still much debate about the specific skill effects. In accordance with the technology of skill formation (Cunha et al. ,2006; Cunha and Heckman, 2007; Cunha and Heckman, 2008), this paper addresses the issue by investigating the relation of parental investments on children's cognitive, mental and emotional skill development in Germany. There is growing evidence for long-term effects of low skill and health levels during childhood on future economic and non-economic outcomes. Cognitive and noncognitive abilities are important predictors for wages, education, crime and health (Borghans et al., 2008; Carneiro et al., 2007; Duckworth and Seligman, 2005).

At the same time, many studies have shown that human capital investments later in life (increasing school quality, teacher/student ratio or participation in active labor market policies) are less efficient than earlier investments (Carneiro and Heckman, 2003). Our primary goal is to address the issue of the optimal timing of investments regarding different types of skills during childhood. Our analysis enriches the research by following infants from birth until the age of 11 years using reliable psychometric measures of skills as well as of parental investments. Analysing this issue right from the beginning is of utmost interest, because evidence exists for the IQ to be stable by the age of ten years (Schuerger and Witt, 1989). However, most previous studies addressing this issue were unable to follow skill formation from birth on and lacked adequate measures of child skills and home environment. In our data, we have reliable expert ratings of skills and investments in each period during childhood, enabling us to improve on measurement error issues.

Our data contains a variety of measurements of cognitive, mental and emotional skills as well as various measurements of parental investments. This data has been studied recently by Blomeyer et al. (2009), who look at particular measurements and find the measured abilities at preschool age as well as initial risk conditions at birth to be important for performance later in life. This paper improves on this earlier approach by Blomeyer et al. (2009). Instead of only using 2 measurements (one for cognitive and for noncognitive skills), we employ the complete measured information on skills provided by 8 different measurements to proxy latent skills. We estimate a factor model to reduce the multiplicity of measures to a minimum number of latent (unobservable) factors. The identified latent factors are able to isolate different skills and investments from each other, thus reducing measurement error bias. The IQ measured in a test, for example, might not represent the pure cognitive skills, because a person with a high level of persistence and concentration (noncognitive abilities) may also achieve a better performance in an IQ test. Hence the IQ measure alone does not necessarily reflect the pure cognitive ability, but may be altered by noncognitive skills. With the model we introduce in this paper we are able to isolate skills and eliminate the bias that may come from other skills and vice versa. There may of course remain some measurement error that we cannot account for due to other omitted variables.

Upon that we improve on Bloymeyer et al. (2009) by performing separate regression for birth risk groups and gender. Our data permit us to distinguish between children born with organic risk, e.g. low birth weight (LBW) or asphyxia, and children born with psychosocial risk, e.g. low educational level of the parents or early parenthood (for a detailed description of organic and psychosocial risk, see Blomeyer et al. (2008)).

Even though we use advanced skill and investment measurements, we face the problem that our inputs of the technology of skill formation are not exogenous. Families with higher abilities and preferences for higher education are more likely to invest more. Not taking this into account will lead to an overestimation of the effect of parental investments. At the same time, skills acquired one period earlier are potentially endogenous, because they reflect unobserved abilities and preferences; hence, ignoring these issues might cause biased estimates.

Considerable evidence suggests that noncognitive skills are more malleable until later ages, while cognitive skills are not (Borghans et al., 2008; Cunha et al., 2010). However, assessments of skills might depend, at least to some extent, on both cognitive and noncognitive skills. In this study, we deal with this fact by differentiating noncognitive skills in two relatively independent dimensions. We exploit results from cluster and factor analyses to distinguish between mental skills and emotional skills, the former being more and the latter being less correlated with cognitive skills.

Our findings suggest that the importance of previous skills for later skill development (self-productivity) increases with age and differs among skills. It is highest for cognitive skills in each model. We find evidence for sensitive and critical periods of cognitive and mental skills. This implies that parental investments are most effective for both types of skills directly after birth and less effective at age eight (sensitive period). After this age their effects turn statistically insignificant (critical period).

Additional analyses by initial risk group status indicate that children who are born with organic risk have a lower self-productivity and benefit less from parental investments. We also find that boys tend to benefit more from investments in their cognitive skill development, while girls tend to benefit more in their mental skill development. Further, our analyses indicate that cognitive skills are most important for predicting school success, followed by mental skills, while emotional skills are less important.

The rest of the paper is organized as follows. Section 5.2 provides information about critical and sensitive periods and summarizes the previous literature. Section 5.3 describes the data and variables, while section 5.4 describes the method. In section 5.5, we present our estimation results, and section 5.6 concludes.

5.2 Background

The underlying concept of critical and sensitive periods is based on interdisciplinary research on brain development and is incorporated in the technology of skill formation (Shonkoff and Phillips, 2000). Both concepts are based on the pace of adoption of early experience of the biochemistry and architecture of neural circuits (Knudsen, 2004). A critical period is defined as a period during which investments have an impact for a limited time span only. If a child does not receive the appropriate stimulation during this period, it may be difficult or even impossible to develop certain functions later in life. In contrast, in the case of sensitive periods, opportunities to attain certain skills exist that may not exist to the same extent in other periods. However, if chances to acquire these skills were not seized during a sensitive period, there may still be a chance to catch up on these skills later in life to attain the same goal (contrasting for critical periods) (Siegler, 2006).

A typical example for a critical period is language acquisition. Acquiring a language is relatively easy for children up to age of six; afterwards, the acquisition of language skills becomes more and more difficult (Pinker, 1994). Moreover, the United Nations Standing Committee on Nutrition (2006) recently stated that “while undernutrition kills during early life, it usually also leads to a high risk of disease and death later in life”. The “window of opportunity” spans from pre-pregnancy to around 24 months of a child’s age. Health and physical characteristics in adult life are significantly influenced by early life conditions. The human muscle structure, for instance, has a critical period of development before birth and during the first six months of life (Barker et al., 2002).

While critical periods in human development have received a lot of attention in medical and psychological studies, the relation between cognitive (intelligence, memory power and reasoning) and noncognitive (persistence, emotion, adaptability and temperament) skill development and the quality of stimulation in the early home environment has barely been addressed in economic research until now. In consequence, even less attention has been given to the way critical and sensitive periods may differ among heterogeneous individuals and their economic outcomes. However, both concepts have important implications for developing educational policies and the optimal timing of human capital investments.

We extend the existing literature by investigating the relationship between parental investments and skill development depending on the initial risk status. In the economic literature, there are only few studies that focus on critical periods in skill development over the life cycle. For example, the study by Todd and Wolpin (2004) uses the NLSY79 to quantify the impact of the HOME (Home Observation Measurement of the Environment) inputs, school inputs and mothers' ability on children's' achievement. Mothers' abilities and HOME inputs combined explain more than half of the test score gap between individuals, while school inputs and mothers' schooling level account only for a very small part of the test score gap. This finding suggests the importance of early investments for cognitive skill development.

Various studies by Heckman and co-authors investigate critical and sensitive periods based on the technology of skill formation starting at the age of 6 years. Cunha and Heckman (2008), for example, find that parental investments affect cognitive skills more at earlier stages than at later stages, while they affect noncognitive skills more between the ages of six and 13 years. However, one limitation of these studies is that they investigate children's skill development from the age of six years on, a time at which the brain has already developed to a large extent. The data we use follow individuals from birth until adolescence, which gives us the opportunity to examine critical and sensitive periods for cognitive and noncognitive skills, starting at birth. A more recent study for Germany, using the same data, finds that noncognitive skills are more malleable during the first 11 years in comparison to cognitive skills (Blomeyer et al., 2009).

5.3 Data and descriptive analysis

5.3.1 The Mannheim Study of Children at Risk

Detailed data on psychometric skill measures and investments come from the Mannheim Study of Children at Risk, a longitudinal epidemiological cohort study following infants at risk from birth to adulthood.[18] The initial sample contains 382 children (184 boys, 198 girls) born between February

[18] For a more detailed explanation of the study, see Blomeyer et al. (2008) or Laucht et al. (2004).

1986 and February 1988. Infants were selected according to their degree of exposure to organic and psychosocial risks. Organic risk reflects peri- and prenatal complications, such as LBW or asphyxia, while psychosocial risk covers risks related to low socio-economic environments such as a low educational level of the parents or early parenthood. Organic and psychosocial risks were scaled into "no risk", "moderate risk" and "high risk". Children were assigned to one of the nine groups resulting from the two-factorial (3x3) design (see Figure 5.1). All groups have about equal size with a slight oversampling of high-risk combinations and equal gender ratios in all subgroups.

To control for confounding effects of family environment and infant medical status, only firstborn children with singleton births and German-speaking parents were enrolled in the study. Furthermore, children with severe physical handicaps, obvious genetic defects or metabolic diseases were excluded. The medical and psychological examinations of the research waves took place when the children were 3 months, 2, 4.5, 8, 11 and 15 years old and are still going on. Participation rates between the six waves are high, despite the extensive survey procedure, comprising a large number of medical and psychological examinations. 95.3 percent of the infants in the initial level participated.[19] Our working sample amounts to 364 observations. Due to missing data, only 357 observations (88.5%) could be used.

5.3.2 Infant skills

5.3.2.1 Cognitive skills

Cognitive skills include memory power, information processing speed, intellectual power, linguistic skills, motor skills as well as general problem solving abilities (Borghans et al., 2008; Knudsen et al., 2006). In our dataset, measures for cognitive skills are represented by the *IQ*, the *verbal IQ*, the *nonverbal IQ* and the *motor quotient (MQ).* Each test consists of a variety of subtests such as numeracy, memory, receptive and expressive language skills. For the first time in the literature, cognitive tests are assessed from three months until the age of 11 years. The *IQ* was measured in a verbal as well as in a nonverbal dimension from the age of two years onwards, since the development of verbal skills starts between 10 and 14 months (Tracy, 2000). For each period, cognitive skills were standardized (mean 0, std. dev. 1[20]). Means of the original variables in our dataset do

[19] The study was approved by the ethics committee of the University of Heidelberg and written informed consent was obtained from all participating families.
[20] For each age, the cognitive tests were assessed with different psychometric measures. See the appendix for a more detailed description.

not change over time. We use all measurements related to cognitive skills to proxy cognitive skills applying factor analysis.

5.3.2.2 Noncognitive skills

In line with the economic literature, we use different aspects of a child's temperament as a measure for noncognitive skills during childhood. The assessment of noncognitive skills took place in two ways: within a standardized parent-interview and during structured direct observations in four standardized settings on two different days in both familiar (home) and unfamiliar (laboratory) surroundings. All ratings were assessed by trained judges on 5-point rating scales of five temperamental dimensions adapted from the New York Longitudinal Study NYLS (Thomas et al., 1968).[21] Measuring temperamental characteristics at the age of three months already is quite reliable.[22] We use five dimensions of a child's noncognitive skills: *persistence, activity, approach/withdrawal, adaptability and prevailing mood.* In accordance with cognitive skills, all noncognitive skills are standardized (mean 0, std.dev. 1).

Persistence refers to a child's ability to pursue a particular activity and its continuation in the face of obstacles. *Activity* describes the frequency and intensity of motor behavior ranging from being inactive and slow to being overactive and restless.[23] *Approach/withdrawal* describes the initial reaction to new stimuli (e.g. strangers, new food, or unfamiliar surroundings). *Adaptability* denotes the length of time that is needed to be habituated to the new stimuli (at the age of 11 years, also including aspects of manageability such as the ability to cooperate with unpleasant occurrences, e.g. conflicts in the peer group or parental admonitions).*Prevailing mood* describes the general tendency of the child to be in a good or a bad temper.

Besides the personality measures we use, a variety of competing taxonomies coexists. Adult personality is often measured by the Big Five personality traits, consisting of openness, conscientiousness, extraversion, agreeableness and neuroticism (Borghans et al., 2008). In contrast to that, child and developmental psychologists usually focus on temperamental taxonomies that are better suited

[21] At the ages of 3 months and 2 years, the interrater reliability was measured in a preliminary study of 30 children.
[22] Satisfactory interrater agreement was obtained between two raters (3 months: Øκ = 0.68, range 0.51 - 0.84; 2 years: Øκ = 0.82, range 0.52 - 1.00).
[23] For the interpretation it is necessary to adjust the scale of activity. In the original version, the variable has a bipolar scale, which means that an average activity level indicates high noncognitive skills while very high and very low levels rather indicate low noncognitive skills. We transform the scale in such the way that high values indicate a high noncognitive skill level and low values, a small skill level.

to assess the developmental process of personality from infancy to adolescence (Thomas et al., 1968). In order to be able to measure child personality, those taxonomies are usually based on parent interviews and direct observations instead of questionnaires.

Studies exist that try to relate existing temperamental measures to the Big Five (Rothbart et al., 1998). They indicate that temperamental measures highly correlate with of the Big Five personality factors. Our temperamental measure *prevailing mood* is most closely related to neuroticism and agreeableness. *Approach* and *activity* are related to extraversion. *Persistence* correlates the most with conscientiousness. The factor openness however seems barely related to any temperamental measures. .

5.3.2.3 Latent skills

Even though the economic literature recently began to distinguish between cognitive and noncognitive skills, it is still a challenge to disentangle both, because measuring cognitive skills might also capture aspects of noncognitive skills and vice versa (Borghans et al., 2008; Cunha and Heckman, 2009). E.g. typical noncognitive skills, such as the ability to persist and concentrate in performing a task, might improve the tested IQ score and thus lead to overestimation of cognitive skills. For our analysis, it is useful to examine the way characteristics of both skills are related first. Putting all skills into one regression would cause a lot of multicollinearity problems. In order to obtain an overview of how the skills are related, we conduct a cluster analysis.

By applying hierarchical clustering, we group our data into clusters in such a way that objects in the same cluster are similar and the objects in different clusters are distinct. First we calculate the absolute correlations and group the pairs with the highest correlations. Next the pairs that are in close proximity are linked using the information generated in the first step. As objects are paired into binary clusters, the newly formed clusters are grouped into larger clusters until a hierarchical tree is formed. The link where groups in the tree presented in figure 5.2 connect always refers to the smallest correlation to the next cluster, e.g. the smallest absolute correlation between the measurement groups “IQ, MQ” and “persistence, activity” is 0.31[24].

Figure 5.2 reveals three groups when analysing the measurement correlations. It shows that the three noncognitive skills[25] *approach, adaptability* and *prevailing mood* form one group, while *activity* and *persistence* form another group which is more closely related to cognitive skills. The *MQ*

[24] For comparison: the correlations among the measurements can also be looked up in table 5.2b in the Appendix.
[25] For a detailed description of cognitive and noncognitive skills, see sections 5.3.2.1 and 5.3.2.2.

(motor quotient) sorts into the cognitive skill group. Our findings suggest that noncognitive skills seem to include a much more heterogeneous set of skills than cognitive skills.

To overcome the problem of multiple skills measurements described above, we perform a factor analysis to reduce the heterogeneity of variables to a minimum number of latent factors. In a first step, we need to determine the number of latent factors required to reflect the data. Too few factors may not be able to capture the information of the data, while too many factors may be highly correlated with each other and not solve the problem of multiple measurements. To identify the optimal number of latent factors, we compute the number of eigenvalues of the correlation matrix that is greater than 1 in figure 5.3 (Kaiser, 1960). This analysis suggests three latent factors to reflect the data.[26] The result is in line with the groups found in the cluster analysis above. Next we calculate the maximum likelihood estimate of a factor loadings matrix Ω in the factor model:

$$z = \mu + \Omega \cdot f + e \qquad (1)$$

With z being a vector of the variable measurements, μ a constant vector of mean values and Ω a constant 8x3 matrix of factor loadings, because we have 8 measurements and 3 latent factors. f is the vector of standardized and independent common factors with length 3 and e the error term of independent specific factors, which is assumed to be normally distributed. We specify the number of common factors m=3 according to the analysis above and solve for the factor loadings in Ω by maximum likelihood. For a more detailed description of the method see Jöreskog (1967).

Next we rotate the factors to facilitate their interpretation. We use the orthomax-rotation which assumes latent factors to be orthogonal. Even if independence among latent factors is a strong assumption, it eliminates multicollinearity problems in the regressions.[27] Finally, the latent factors are predicted.

After identifying 3 latent factors we still do not know which of them is related to which skill. Thus, we calculate the correlations of measurements and the 3 identified latent factors (Table 5.1). This

[26] A factor analysis revealing only two instead of three factors was also conducted. In this analysis, only cognitive skills and emotional skills are identified. Thus, important noncognitive traits like persistence and activity are not taken into account.

[27] The orthomax rotation aims at obtaining common factors that are composed of only a few variables (Frank and Todeschini, 1994). As an orthogonal transformation, the rotated factors will be uncorrelated. The variance of the squared loadings of the 3 factors on all the 8 measurements in the factor matrix Ω is maximized. This has the effect of differentiating the original measurements by the extracted factor. Each factor will tend to have either very large or small loadings on a particular measurement. Alternatively, we performed an oblique promax-rotation which generated very similar results. In this rotation latent factors will be correlated. In our estimation this resulted in coefficients being slightly greater due to higher multicollinearity among factors.

yields three different types of skills: cognitive, mental and emotional skills (see Table 5.1). Non-cognitive skills are split into two dimensions: mental and emotional skills. Mental skills are a mix of the optimal activity level and persistence.[28] Emotional skills sum up traits like adaptability, approach and prevailing mood. Mental skills are more related to cognitive skills, while emotional skills form a completely different group. Results presented in Table 5.1 show that the first factor is highly correlated with IQ, the second factor is highly correlated with persistence and activity and the third factor is highly correlated with approach, adaptability and prevailing mood.

Descriptive evidence in Figure 5.4 indicates that children born with neither organic nor psychosocial risks have on average significantly higher cognitive skills compared to children born with either risk. Organic risk seems to affect cognitive abilities much stronger than psychosocial risk during childhood. Moreover, for children born with the highest degree of both types of risk, cognitive skills are lowest in comparison to all other risk combinations throughout childhood. However, the variance within this high-risk group is larger compared to other cells of the matrix, in particular the risk to have very low cognitive skills considerably.

Figure 5.5 and 5.6 present the distribution for mental and emotional skills, respectively. Differences in the mean values of mental skills are significantly lower among children born with psychosocial risk than among children born with organic risk throughout childhood. It is also important to note that the mean of mental skills is significantly lower if children were born with a combination of both risk types compared to any other case. The variation in mental skill levels increases with both the degree of organic and psychosocial risk. In contrast to mental skills, initial risk seems to barely have an impact on the development of emotional skills (see Figure 5.6).

To sum up, the descriptive evidence suggests that cognitive and mental skills are more related to each other during childhood than to emotional skills. Organic risk seems to have an adverse effect rather on cognitive skills and psychosocial risk seems to rather affect mental skills negatively. Both risks enhance each other in combination, which is in line with the existing literature. Almond et al. (2009) for example find prenatal exposure to Chernobyl fallout to negatively affect cognitive skills later in life and children of low educated parents (in our data children rather prone to psychosocial risk) to be more vulnerable. On the other hand, initial risk seems barely related to emotional skills.

[28]Mental skills are closely related to mental health (ADHD).

5.3.3 Parental investments

Already in the early 80s, psychological studies indicated a strong link between cognitive abilities and HOME as a relevant measure for preparing and fostering abilities starting in early childhood (Bradly, 1982). Instead of solely observing family income as a measure of parental investments, we focus on the quality of the home environment which also includes aspects of the parent-child relationship in this study using a modified version of the original HOME inventory (Bradly and Caldwell, 1980). To proxy the latent variable "parental investments", we use all items of the HOME as a measurement at the ages of 3 months, 2 years, 4.5 years, 8 and 11 years. The HOME consists of six subscales: (1) emotional and verbal responsibility of the mother, (2) acceptance of the child, (3) organization of the environment, (4) provision of appropriate play materials, (5) maternal involvement with the child and (6) opportunities for variety in daily stimulation. The number of items varies between 38 in the first period (age 3 month) and 81 at the age of 11 years. Similar to the skill measurements, all items of the HOME score are also assessed by trained interviewers. The distribution of parental investment for each risk group and age is presented in Figure 5.7.

Parental investments are also standardized by (0, 1). Figure 5.7 shows that they are quite high for children with no psychosocial risk and for children with low or high organic risk, on average. In particular, it seems that parental investments are slightly higher for children who were born with a high organic risk, which could imply that parents try to compensate initial organic risk. The reverse is true when we regard mean investments for children born with psychosocial risk. These systematic differences for children born with psychosocial risk demonstrate the importance of initial conditions followed by low parental investments. Moreover, it is obvious that the parental investments are relatively stable during childhood, in particular for children born with high psychosocial risk. However, there is still a large variation between the 90th and 10th percentile in mean parental investments.

5.4 Methods

As discussed in previous sections, we analyse how parental investments influence cognitive and noncognitive skill developments during five crucial periods of early childhood (at the ages of 3 months, 2 years, 4.5 years, 8 years, 11 years, respectively). In accordance to Cunha and Heckman (2007), we estimate a linear specification of the technology of skill formation. We assume an immediate impact of investments on skills in the production function in line with Cunha et al. (2006), because the time between our research waves is two years and more. Instead of using noncognitive skills as one single measure, we differentiate between mental and emotional skills:

$$S_t^c = f_t(S_{t-1}^c, S_{t-1}^m, S_{t-1}^e, I_t)$$

$$S_t^c = a_0^c + a_{1,t-1}^c S_{t-1}^c + a_{2,t-1}^m S_{t-1}^m + a_{3,t-1}^e S_{t-1}^e + b_t^c I_t^c + \eta_t^c \tag{5.2a}$$

$$S_t^m = f_t(S_{t-1}^c, S_{t-1}^m, S_{t-1}^e, I_t)$$

$$S_t^m = a_0^m + a_{1,t-1}^c S_{t-1}^c + a_{2,t-1}^m S_{t-1}^m + a_{3,t-1}^e S_{t-1}^e + b_t^m I_t + \eta_t^m \tag{5.2b}$$

$$S_t^e = f_t(S_{t-1}^c, S_{t-1}^m, S_{t-1}^e, I_t)$$

$$S_t^e = a_0^e + a_{1,t-1}^c S_{t-1}^c + a_{2,t-1}^m S_{t-1}^m + a_{3,t-1}^e S_{t-1}^e + b_t^e I_t^e + \eta_t^e \tag{5.2c}$$

Where S_t^c, S_t^m and S_t^e denote cognitive, mental and emotional skills in period *t* and I_t denotes parental investment in their child's skills for each period *t*. In accordance to Cunha and Heckman (2007)[29], we define critical and sensitive periods as follows:

Period *t* is a critical period for S_t^k with $k = c, m, e$ if:

$$\begin{aligned} &\frac{\partial\ S_t^k}{\partial\ I_t} \neq 0 && \qquad\qquad \mathit{for\ \ some}\ S_{t-1}, I_t = i_t \\ &\mathit{but} \\ &\frac{\partial\ S_{t+j}^k}{\partial\ I_{t+j}^c} = 0 \quad \mathit{with}\ j > 0 && \qquad\qquad \mathit{for\ \ all}\ \ S_t, I_t = i_t \end{aligned} \tag{5.3}$$

Period *t* is a sensitive period for S_t^k with $k = c, m, e$ if:

$$\frac{\partial\ S_{t+j}^k}{\partial\ I_{t+j}}\Big| S_{t+j} = \overline{S},\ I_{t+j} = i \ < \ \frac{\partial\ S_t^k}{\partial\ I_t}\Big| S_{t-1} = \overline{S},\ I_t = i \qquad\qquad \mathit{for}\ j \neq 0 \tag{5.4}$$

A c*ritical* period describes a time span *t* for cognitive (mental or emotional) skill development if parental investments are productive in period *t*, but not in any other period t+j≠*t* (see equation (5.3)). A period *t* is a *sensitive period* relative to period t+j with j≠0 for cognitive (mental or emotional) skill development if, at the same level of skills $\overline{S}$ and inputs i, investment is more productive during the time span *t* than during any other time span t+j≠*t*. Using a linear specification, we can observe critical and sensitive periods for cognitive, mental and emotional skills. Moreover, it is

[29] See the web appendix of Cunha and Heckman (2007) for more detailed discussion on the definition of critical and sensitive periods

possible to observe self-productivity and direct-complementarities among these three skills. Self-productivity means that the formation of skills is the more productive the higher the stock of skills at the previous period. In accordance to self-productivity, direct-complementarities apply if cognitive skills are productive for the formation of noncognitive skills at previous periods and vice versa. Instead of using single proxies for cognitive and noncognitive skills, we use cognitive test scores and behavioral measures as well as parental inputs as indicators for latent skills and latent parental investments.[30] Equations (5.5a) - (5.5d) describe the measurement equations for all skills (*Y)* and parental investments (*X)* in each period during childhood:

$$Y^{c}_{j,t} = \alpha^{c}_{j,t} + \beta^{c}_{j,t} S^{c}_{t} + \varepsilon^{c}_{j,t} \qquad \forall\, t = 1,...,5 \tag{5.5a}$$

$$Y^{m}_{j,t} = \alpha^{m}_{j,t} + \beta^{m}_{j,t} S^{m}_{t} + \varepsilon^{m}_{j,t} \qquad \forall\, t = 1,...,5 \tag{5.5b}$$

$$Y^{e}_{j,t} = \alpha^{e}_{j,t} + \beta^{e}_{j,t} S^{e}_{t} + \varepsilon^{e}_{j,t} \qquad \forall\, t = 1,...,5 \tag{5.5c}$$

$$X^{i}_{j,t} = \alpha^{i}_{j,t} + \beta^{i}_{j,t} I^{i}_{t} + \varepsilon^{i}_{j,t} \qquad \forall\, t = 1,...,5 \tag{5.5d}$$

Instead of using the unobserved vectors for skills and parental investments *S* and *I*, we use measurements *j* for each skill and investment at each stage. We normalize the first *β* to $\beta^{c}_{j,t} = \beta^{m}_{j,t} = \beta^{e}_{j,t} = \beta^{i}_{j,t} = 1$. Substituting measurement equations (5.5a) – (5.5d) into equations (5.2a) - (5.2b) yields:

$$y^{c}_{1t} = \gamma^{c}_{1,t-1} Y^{c}_{1,t} + \gamma^{m}_{2,t-1} Y^{m}_{1,t-1} + \gamma^{e}_{3,t} Y^{e}_{1,t-1} + \gamma_{4,t-1} X_{1,t} + u^{c}_{t} \tag{5.6a}$$

$$y^{m}_{1t} = \gamma^{c}_{1,t-1} Y^{c}_{1,t} + \gamma^{m}_{2,t-1} Y^{m}_{1,t-1} + \gamma^{e}_{3,t} Y^{e}_{1,t-1} + \gamma_{4,t-1} X_{1,t} + u^{m}_{t} \tag{5.6b}$$

$$y^{e}_{1t} = \gamma^{c}_{1,t-1} Y^{c}_{1,t} + \gamma^{m}_{2,t-1} Y^{m}_{1,t-1} + \gamma^{e}_{3,t} Y^{e}_{1,t-1} + \gamma_{4,t-1} X_{1,t} + u^{e}_{t} \tag{5.6c}$$

The error term of each equation (5.6a) – (5.6c) u_t includes all errors ε from (5.5a) – (5.5b) and the error term from equation (5.2a) – (5.2c): For example, the error term u^{c}_{t} for equation (5.6a) is:

$$u^{c}_{t} = \varepsilon^{c}_{1,t} - \gamma^{c}_{1,t-1}\varepsilon^{c}_{1,t-1} - \gamma^{c}_{2,t-1}\varepsilon^{m}_{1,t-1} - \gamma^{c}_{3,t-1}\varepsilon^{e}_{1,t-1} - \gamma^{c}_{4,t}\varepsilon^{i}_{1,t} + \eta^{c}_{t}$$

We estimate equations (5.6a) – (5.6c) by least squares. The production functions with unbiased parameters of interest γ can be indentified under the assumptions that: (1) the errors *ε* have a mean of zero and are independently distributed across individuals and over time, (2) the errors *ε* have a mean of zero and are independently distributed over latent skills and investments for all time periods and (3) the errors *ε* are mutually independent from each other (Cunha and Heckman, 2008).

[30] See section 5.3 for a detailed description.

There might be two problems with those assumptions. First, parental behaviour cannot be observed beyond the observation period. It could be endogenous depending on certain characteristics of the child. Other factors such as peers or the day care of grandparents may be important, but are not directly observed. The genetic endowment may also be a relevant issue, for which we are unable to account.

Secondly, when measuring skills and investments, the variables could be recorded with random and/or systematic error. In the case of systematic errors, the errors are not independent and uncorrelated and the assumptions above do not hold. This can result from an interviewer or respondent bias.

While we cannot completely control for all of the observed and endogenous aspects mentioned above, we expect the measurement error in our data to be relatively small for two reasons. First, the interviewers were trained for each interview and for each assessment, for the HOME score as well as for psychometric tests. Often, different interviewers performed the same assessments repeatedly. The interrater reliability defines the correlation of the test result for one individual between interviewers. In most cases, this score has a correlation which varies between 0.6 and 0.8. Secondly the respondent bias due to misunderstanding questionnaires is marginal in our data, because the measures were commonly assessed by the trained interviewers. The assessments of skills and investments occurred in different standardized surroundings and on different days. Additionally, the quality of the assessments is high, because trained interviewers observe children and their parents from birth on. This results in a trustful relationship and reduces non-response of difficult and critical questions leading to a high data quality.

In the next section, we illustrate our estimation results. Therefore, we separately estimate equations for each latent skill (cognitive, mental and emotional) at each stage during childhood (2 years, 4.5 years, 8, years and 11 years

5.5 Results

5.5.1 Skill production function with cognitive, mental and emotional skills

Figure 5.8 presents our estimates for cognitive, mental and emotional skills during the first 11 years of life. We use bootstrapped standard errors with 500 replications (Efron and Tibshirani, 1993). The upper row of graphs shows the estimation results for self-productivity of cognitive skills (cognitive→cognitive) and direct-complementarities between cognitive and mental as well as between cognitive and emotional skills (cognitive→mental and cognitive→emotional). Graphs in the second row illustrate estimation results for self-productivity of mental skills (mental→mental), direct complementarities between mental and cognitive skills (mental→cognitive) and direct-complementarities between mental and emotional skills (mental→emotional). The third row presents estimation results for emotional skills: firstly direct-complementarities between emotional and cognitive skills and between emotional and mental skills (emotional→cognitive and emotional→mental), secondly self-productivity for emotional skills (emotional→emotional). The bottom row shows estimation results for the impact of parental investment on each skill, respectively. For the following analysis, we structure the presentation of our estimation results in the same way.

Our results indicate different patterns for the development of skills during childhood. All skills have in common that the stock of skills acquired during previous periods is essential for the skill formation in later periods with coefficients being significantly greater than zero (cognitive→cognitive, mental→mental and emotional→emotional). In fact, self-productivity steadily increases during childhood; however, the estimates suggest that self-productivity for mental skills is important only after the age of four. In contrast to that, even innate cognitive and emotional skills contribute to their further development. Self-productivity is the largest for cognitive skills (cognitive→cognitive).

Regarding direct-complementarities between these skills, it is obvious that cognitive skills foster mental skills and vice versa (e.g. cognitive→mental and mental→cognitive in figure 5.8), but neither cognitive nor mental skills have an effect on the development of emotional skills (e.g. cognitive→emotional and mental→emotional). The HOME seems to influence cognitive and mental skills (home→cognitive and home→mental), while emotional skills are not affected by the HOME score (home→emotional). Surprisingly, regarding the impact of the HOME scores on cognitive and on mental skills, both behave quite similarly. The estimated effect of the HOME score is higher directly after birth compared to the impact of the HOME score two years later and 4 years later, while it becomes insignificant at age eight. Moreover, the effect is nearly twice as large for mental skills compared to cognitive skills.

The coefficient of the investment on cognitive skills at the age of 2 years is approximately 0.13. For the 50th percentile of the cognitive skill distribution, an increase in the HOME score by a standard deviation corresponds to an increase to the 56th percentile. For the mental skill distribution the coefficient of 0.27 even corresponds to an increase from the 50th to the 66th percentile. This example illustrates the shaping role of parental investments in early childhood.

The results also imply that there are differences in the effectiveness of investments, even amongst noncognitive skills, since mental skills are malleable, while emotional skills seem not to be affected by the HOME score (home→mental and home→emotional). This result suggests that other factors such as genetic endowment or peers are more important for the development of emotional skills.

To identify critical periods we look at the time span when investments are significantly different from zero. For we find the time span until the age of 4.5 years to be a critical period for cognitive skills and the time span until the age of 8 years to be a critical period for mental skills. No critical period is found for emotional skills.

To identify sensitive periods we need to check if $b_t^k \neq b_{t+j}^k \; with \; j \neq 0 \; and \; k = c, m, e$ for each *j* (see equation 5.4). This is done by estimating b_t^k and b_{t+j}^k as described in section 5.4 and bootstrapping the difference. We perform 500 repetitions and check the hypothesis if $b_t^k - b_{t+j}^k > 0$. If the hypothesis cannot be rejected, then *t* is a sensitive period. We find the age of ages 2 years and 4.5 years to be a sensitive period relative to the age of 8 years for cognitive skills (Table 5.2). For mental skills we find the age of 2 years to be a sensitive period relative the age of 8 and 11 years and the age of 4.5 years to be sensitive relative to the age of 11 years. For emotional skills we do not find a sensitive period.

Our sample is not representative for the overall population, due to an oversampling of children at risk. Hence, we re-estimate the models for a weighted representative sample (for the calculation of the weights, see Table 5.1b in Appendix). Our data contains 110 individuals from a representatively selected sample. To generate weights, we calculate the fraction of the representative observations on the overall observations for each risk group. The results are reported in Figure 5.9. The baseline pattern is not affected when using a (weighted) representative sample instead of the original (risk) sample. However, if we take oversampling of organic risk into account (c.p: Table 5.1b in the Appendix), the impact of the HOME score on cognitive skills increases and becomes more similar to the HOME score impact on mental skills.

This indicates that a high organic risk might have an adverse effect on the impact of the HOME score on cognitive skills and leads to an underestimation of the HOME impact on cognitive skills (home→cognitive) in the unweighted sample. This result is confirmed by the analysis in Section 5.5.2, where organic risk negatively affects cognitive skills, but not mental skills.

The coefficient of the investment on cognitive skills at the age of 2 years now is approximately 0.19. For the 50th percentile of the cognitive skill distribution an increase of the HOME score by a standard deviation corresponds to an increase to the 59th percentile. For the mental skill distribution the same increase with a coefficient of 0.2 corresponds to an increase from the 50th to the 61st percentile.

For the weighted sample we also find a significant positive relation of the HOME score with emotional skills in late childhood, which suggests that some (noncognitive) skills may still be malleable during adolescence. We identify the time span until the age of 8 years to be a critical period for cognitive and mental skills and the age of 11 years to be a critical period for emotional skills. The age of 2 years is a sensitive period relative to the age of 8 and 11 and the age of 4.5 years sensitive to the age of 11 for cognitive skills (Table 5.2). For mental skills the ages of 2 and 4.5 years are a sensitive period relative to the age of 11 years. The age of 11 years is the sensitive period relative to the age until 4.5 years.

5.5.2 Skill production function with cognitive, mental and emotional skills by initial risk status

In addition to the results presented in the section before, we differentiated by the initial risk-group status. In order to assess how the results might be affected by risk-group status at birth, we re-estimate our models presented in the previous section for three different risk groups (see Figure 5.10). First, we are interested in the skill development of children who were born with organic (medium or high) risk. Secondly, we compare the skill development of children who were born with psychosocial (medium or high) risk. And thirdly, we re-estimate all models for children with combined risks. Clearly, our sub-sample size varies between 80 and 160 observations, leading to less precise estimates. However, our intention is merely to get an idea of how initial conditions matter in the skill developmental process during childhood. .

The main pattern of Figure 5.10 (home→cognitive) is that we find significant effects of the HOME score on cognitive skill development during childhood only for children with psychosocial risk. For children born with organic risk, the HOME score seems to have no effects on cognitive skill development which indicates that organic risk impairs skill development during childhood. It is essential to note that children born with organic risk often tend to experience an above average amount of parental investments (compare Figure 5.7). However, this adverse initial organic condition seems to remain persistent, even with high parental investments, at least during the first 11 years of life.

In contrast, being part of a high risk group barely seems to have an effect on HOME score impacts on mental skill development and differences are generally insignificant (home→mental). Emotional skills, on the other hand, appear to be positively influenced by high HOME scores in the group with high psychosocial risk during late childhood (home→emotional). Just like for cognitive skill development, high organic risk seems to have adverse effects. In all risk groups, the HOME score has a significantly positive effect on mental skill development.

Self-productivity tends to be less pronounced among children born with organic risk compared to psychosocial or combined risk groups when regarding cognitive and mental skills (see cognitive→cognitive, mental→mental and emotional→emotional). For emotional skills, the group of children born with combined risk indicates a high self-productivity for most stages during childhood. For cognitive skills, we find self-productivity to be positive at least from the age of two years on for all risk groups. For mental and emotional skills, self-productivity is significant from the age of four on.

The adverse effects of organic risk on skill development in our results are consistent with findings from the low birth weight (LBW) literature, showing lasting impacts of LBW in school and even in the labor market (Oreopoulos et al., 2008) In contrast, children born with psychosocial risk mostly benefit from parental investments throughout childhood.

Our estimates display the following pattern: organic risk at birth is much more harmful for cognitive skill development than psychosocial risk during childhood. Even in the case of high parental investments, these are less effective for the cognitive skill development of children born with organic risk compared to children born with psychosocial risk. This is in line with findings which show that organic risk such as LBW significantly reduces outcomes later in life (Almond, 2006; Black et al., 2007). For mental skills, parental investment matters more for children born with organic risk than for children born with psychosocial risk at later ages. For emotional skills, we find no significant impact of parental investments depending on status and stages. Even in these small samples, our results indicate that initial conditions matter throughout childhood. In particular, organic risk seems more detrimental for the development of cognitive skills relative to noncognitive skills.

5.5.3 Skill production function with cognitive, mental and emotional skills by gender

Gender differences in the development of skills exist but seem to be quite small (see Figure 5.11). We observe evidence of self-productivity for cognitive, mental and emotional skills in both girls and boys (see cognitive→cognitive, mental→mental and emotional→emotional). Regarding cognitive skills, self-productivity is larger from age four on in girls, but at the end of childhood, gender differences seem to vanish (cognitive→cognitive). For mental skills, self-productivity is larger for boys, while, generally, self-productivity for emotional skills is quite larger for girls.

Cognitive skills foster mental and emotional skills equally in both genders (cognitive→mental, cognitive→ emotional). The cross-effects between mental and emotional skills are insignificant for girls and boys. In line with previous results, there are no significant gender-specific effects of emotional skills on cognitive and mental skills.

For boys, the effect of parental investment on cognitive skills tends to decrease during childhood. Afterwards, cognitive skills seem to remain unaffected by parental investment. In contrast, parental investments apparently have a smaller impact on a girl's cognitive skill development throughout childhood compared to boys. Gender-specific differences also arise in mental skills. Here, girls benefit remarkably more than boys from parental investments at each stage during childhood (see last row). To both genders equally applies that emotional skills are not influenced by parental investments.

5.5.4 Relationship between skills and educational performance

In this section, we address the well-known finding that skills attained during childhood are important predictors of school success. First, we look at the relationship of cognitive, mental and emotional skills attained during childhood with grades in math, German and the first foreign language at age 11 and 15 using an aggregate grade score (see Table 5.3).[31] The distribution of school grades is presented in Figure 5.1a, Appendix. Secondly, we focus on the probability to attain a high school degree (Abitur, see Table 5.4).

Given the assumptions of section 5.4, we can estimate a prediction of school achievement. This gives some hint on how important early skills are and which kind of skills matter. The results indicate that cognitive and mental skills are important predictors of school grades, and the prediction increases with age. Cognitive skills significantly predict school grades already at the age of three months. From age two on, children with high mental skills perform significantly better in school. In contrast, emotional skills seem to be less important for school success. If we aggregate the coefficient for cognitive, mental and emotional skills (0.21+0.15+0.07) attained at the age of 11 years, grades at school would improve by nearly half a grade. This finding supports evidence that both cognitive and noncognitive skills equally seem to contribute to economic success later in life (Borghans et al., 2008; Heckman, 2008).

Table 5.4 presents the relationship between cognitive, mental and emotional skills and the probability of attaining a high school degree. In accordance with school grades, our results suggest that cognitive and mental skills are the most important skills for school success. An increase in cognitive and mental skills by one standard deviation increases the probability of attaining a high school degree by seven percentage points. The probability increases with age. For example, the marginal probability of attaining a high school degree is 0.18 percentage points at age 11. Emotional skills obtained at age two and 4.5 are predictors for the secondary school track, but later on, they are no longer important.

Altogether, these results show two important patterns. First, even skills observed directly after birth are related to later school achievement. Due to the relevance of self-productivity for cognitive, mental and emotional skills (see results from previous sections), this result implies that inequality starts very early and increases during childhood. Secondly, cognitive and mental skills, which comprise, for example, the ability to pay attention, are more important for school achievement than emotional skills.

5.6 Conclusion

This study provides new evidence regarding the skill formation process during childhood by separating noncognitive skills in mental and emotional skills due to their heterogeneity by employing a factor analysis to reduce the multiplicity of inputs. We follow children from in utero conditions until adolescence regarding their skills and environments using the Mannheim Study of Children at Risk.

[31] Often, educational studies use test scores like PISA or PIRLS as a measure of student performance. However, we are unable to observe more objective students tests within the data.

The HOME score (Home Observation Measurement of the Environment) is used to measure parental investments, starting at birth (Bradly, 1982). The HOME consists of several items measuring the quality of the home environment, such as the maternal involvement with the child, acceptance of the child, play materials, variety in daily stimulation and others.

We find the distributions of mental and cognitive skills to be related and emotional skills to be more distinct. Our estimation results indicate that early investments measured by the HOME score significantly increase the levels of cognitive and mental skills, but not of emotional skills. In the weighted sample, for example, the coefficient of the investment on cognitive skills at the age of 2 years is approximately 0.19. For the 50th percentile of the cognitive skill distribution an increase in the HOME score by a standard deviation corresponds to an increase to the 59th percentile. For the mental skill distribution the same increase with a coefficient of 0.2 corresponds to an increase from the 50th to the 61st percentile.

The estimates further suggest that improvements in early skills raise the stock of skills at later stages during childhood. This phenomenon is described as "self-productivity" (Cunha et al., 2006). We find self-productivity to increase with age, being higher for cognitive skills than for mental and emotional skills. This result is in line with the literature suggesting noncognitive skills to be more malleable than cognitive skills (Cunha and Heckman, 2007). Additionally, cognitive skills are observed to foster the development of mental skills and vice versa. This phenomenon is described as "direct-complementarity". Due to self-productivity and direct-complementarity early investments can have a long lasting effect on skill levels during later childhood.

For cognitive and mental skills we can indentify early childhood (until the age of 4.5 years) to be a sensitive period relative to late childhood (from the age of 8 years on): in early childhood the HOME score impact on both skills is significantly higher than in late childhood.

Our study also provides evidence for critical periods: if we do not take sample weights into account, the HOME score impact becomes insignificant at the age of 4.5 years for cognitive skills and at the age of 8 years for mental skills. When we take sample weights into account the HOME score impact becomes insignificant for both skills at the age of 8 years. Thus, the time span until the age of 4.5 years (8 years, respectively) is a critical period for cognitive skills and the time span until the age of 8 years a critical period for mental skills.

In contrast to that, we find no impact of the HOME on emotional skills during the entire 11 years of childhood. One should note that our results refer only to specific aspects of parental investments measured by the HOME such as organization of physical environment or parental behaviour during the observation period. It does not generalize with regard to other kinds of parental investments. Other factors such as peers or the day care of grandparents may be important, but are not directly observed. The genetic endowment may also be a relevant issue, for which we are unable to account.

Additional analyses by initial risk group status indicate that children who were born with organic risk have a lower self-productivity and benefit less from parental investments. Parental investments, for instance, have no impact on cognitive skills, neither at birth nor at the end of childhood. In contrast, parental investments have the largest effect on cognitive skill development among children born with initial psychosocial risk, but the lowest impact regarding emotional development. This finding supports the hypothesis that children born with low birth weight or born preterm tend to be less able to catch up these adverse initial conditions. Given this finding, investments during pregnancy are essential for the further development. This is in line with studies indicating the adverse effects of maternal smoking, health problems, depression and SES during pregnancy (Barker et al., 2002).

Gender specific differences regarding the skill formation process are small. The amount of self-productivity and direct-complementary is quite similar. Differences between girls and boys arise when observing the effect of parental investments. Here, boys gain more in terms of cognitive skill development, while girls gain more with respect to their mental skill development. Finally, we actually ask how important cognitive, mental and emotional skills are for school success. Our results indicate that cognitive skills are most important for explaining school success, followed by mental skills, while emotional skills are less important. Even at the age of three months cognitive skills are already an important predictor for school success. This relationship increases with age.

Our study suggests that policies that aim to increase the human capital of a society or to reduce lifetime inequality should try to improve conditions for (disadvantaged) children very early in life starting before birth (Heckman, 2008). Even pregnancy may be a critical period in some cases. Adverse in utero conditions (organic risk) seem to negatively affect skill development during the later stages of childhood. Thus skill gaps seem to arise immediately after birth and increase during childhood long before formal education starts. Skills become stable at the ages of 8 to 11 years which is shown by the high self-productivity of skills that we estimate. Initial skill inequality is likely to persist later in life. This result is confirmed by the fact that childhood skills are reliable predictors for school success during adolescence.

Our results are in line with Cunha and Heckman (2007), who emphasize the shaping role of early childhood. They confirm the importance of in utero conditions for the outcomes of later periods

(Almond, 2006; Doyle et al., 2009). We add evidence to the existing literature by using a dataset containing very rich and accurate measurements of skills and environmental aspects. In contrast to many previous studies we can continuously follow the children from birth on until adolescence in a panel dataset. We improve on Blomeyer et al. (2009) by indentifying latent factors for skills from a variety of skill measurements and account for birth risk and gender.

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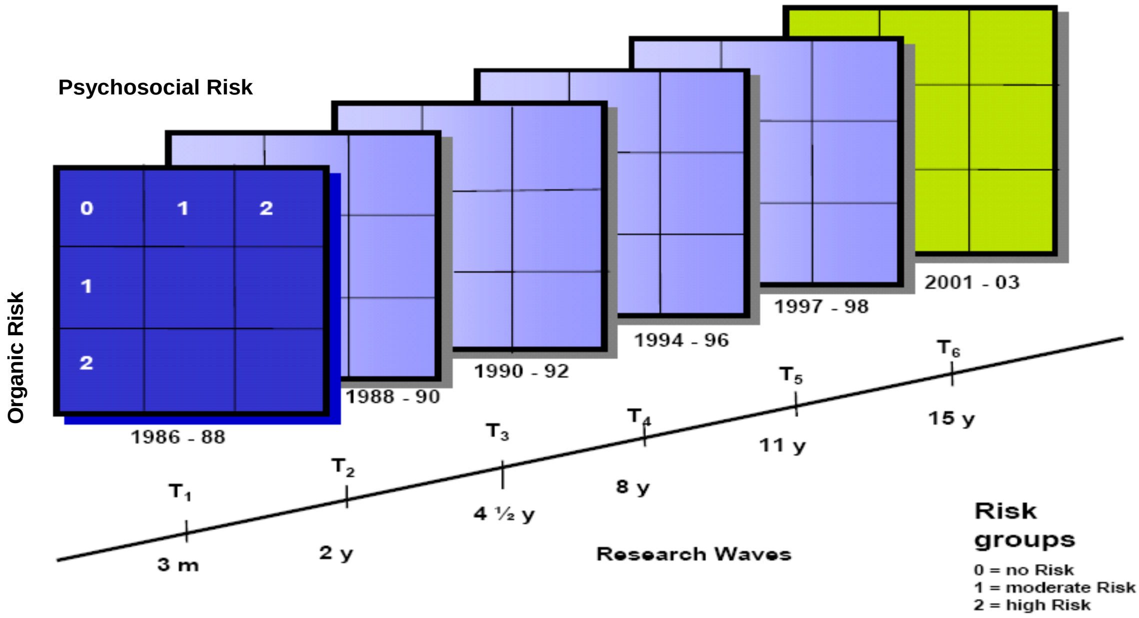
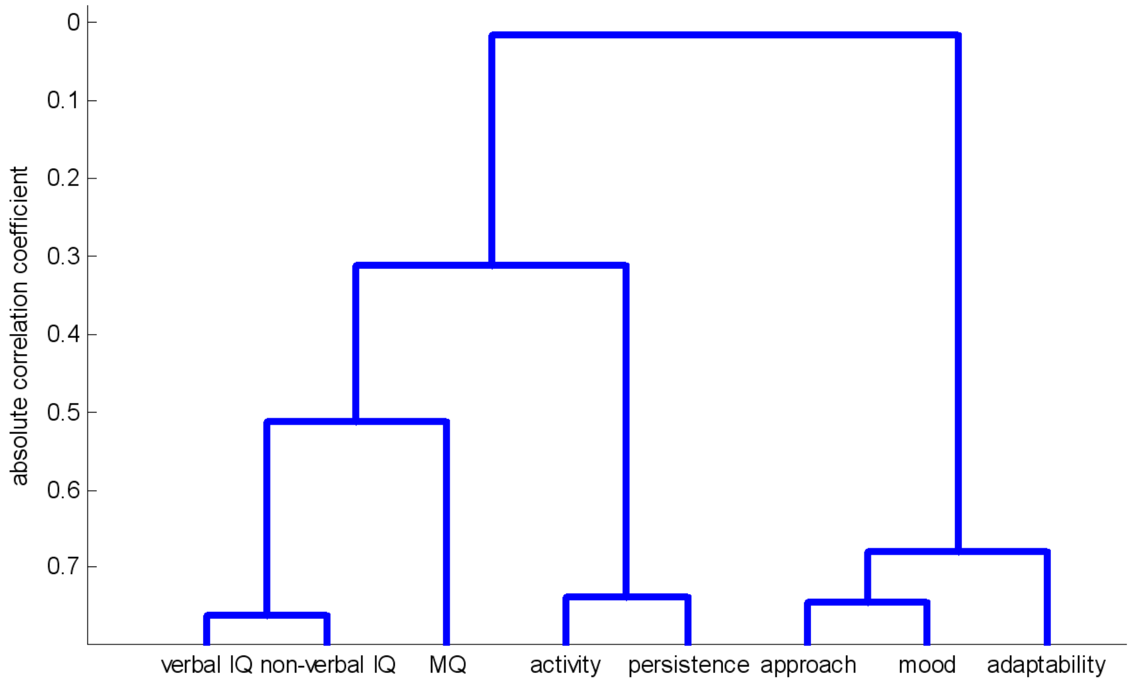
Figures:

Figure 5.1: The Mannheim Study of Children at Risk



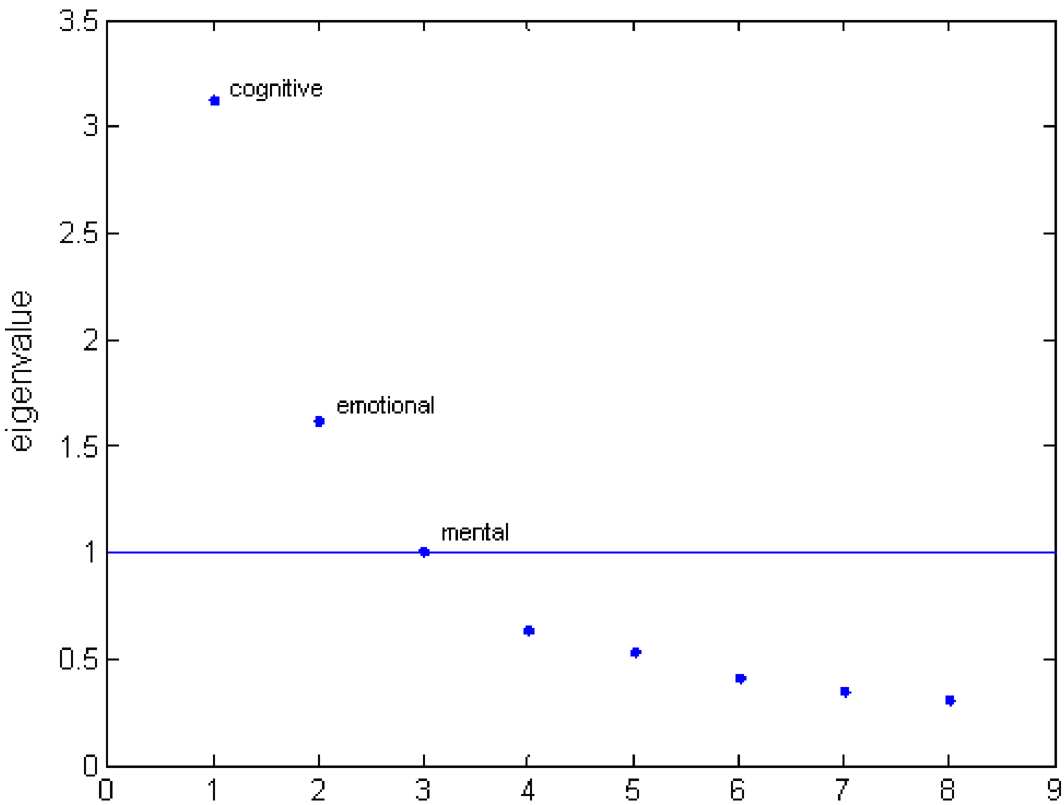
Source: Mannheim Study of Children at Risk.

Figure 5.2: Cluster analysis



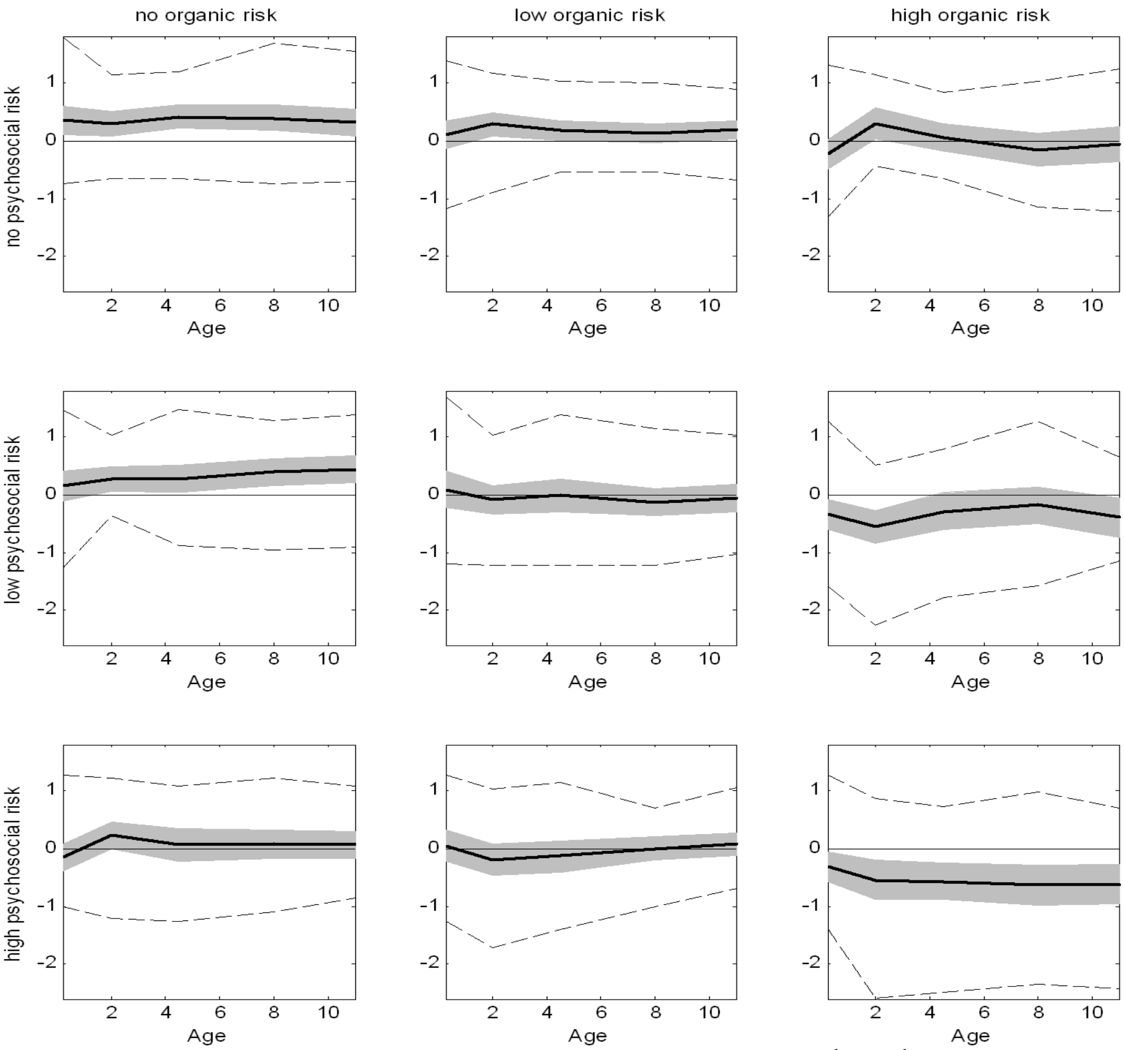
Source: Mannheim Study of Children at Risk. Own calculations.

Figure 5.3: Eigenvalues of the correlation matrix



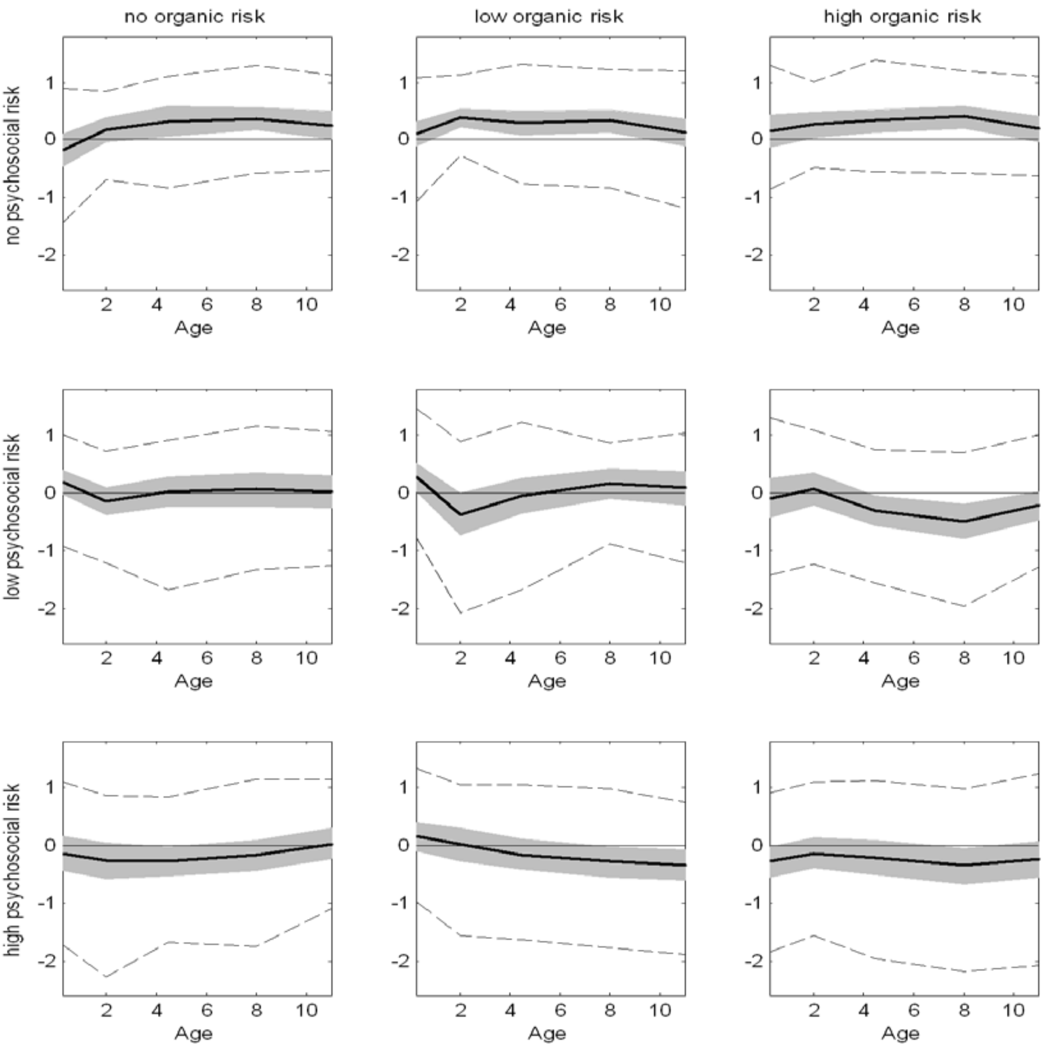
Source: Mannheim Study of Children at Risk. Own calculations.

Figure 5.4: Distribution of cognitive skills by age and risk status



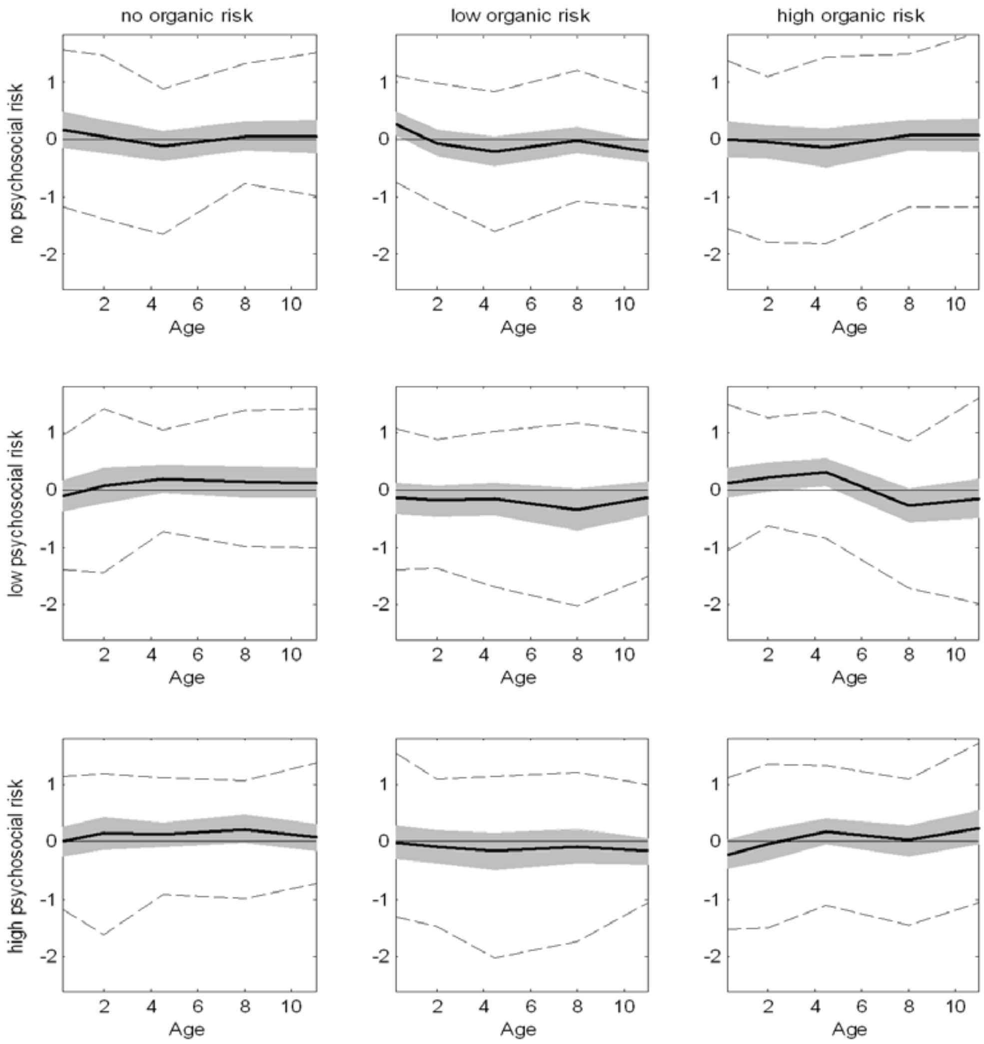
Note: Mean (and grey-shaded 95 % confidence bounds), the 10th, 90th percentile of standardized cognitive skills.
Source: Mannheim Study of Children at Risk. Own calculations.

Figure 5.5: Distribution of mental skills by age and risk status



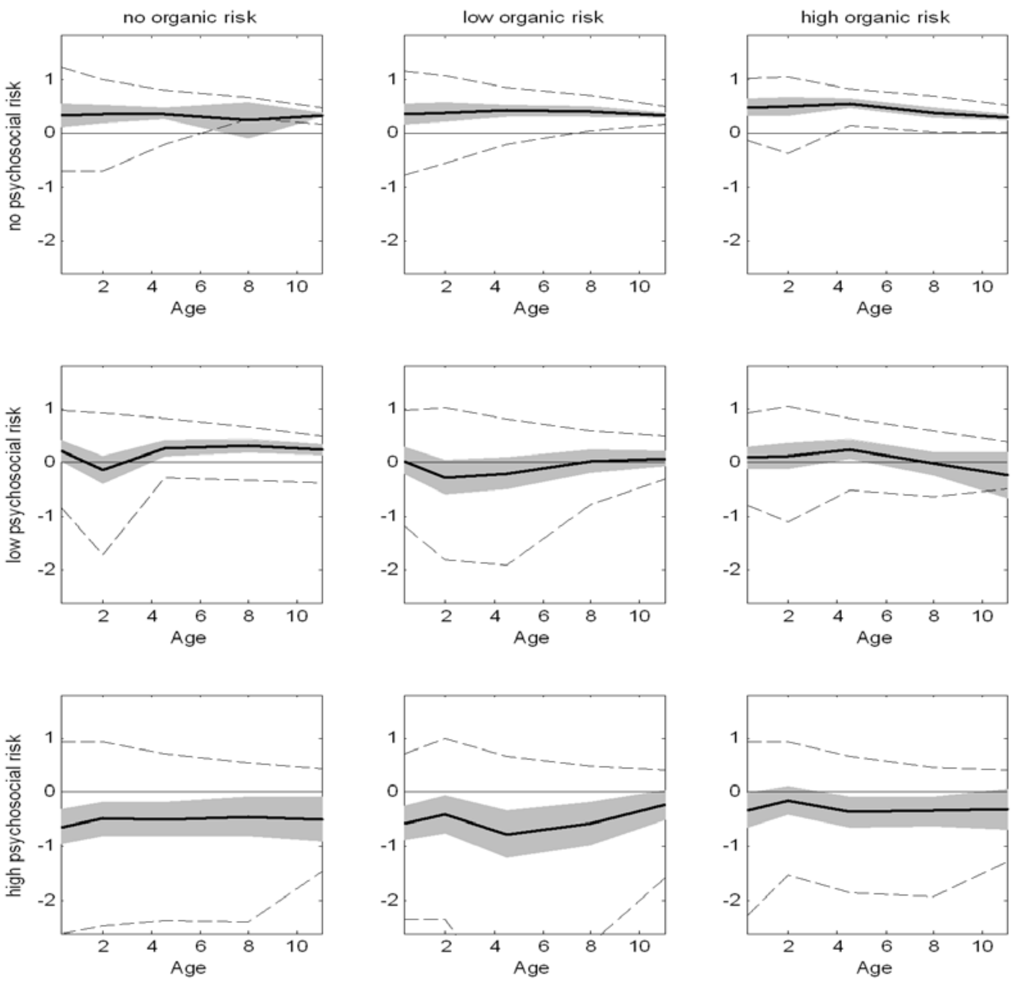
Note: Mean (and grey-shaded 95 % confidence bounds), the 10th, 90th percentile of standardized mental skills.
Source: Mannheim Study of Children at Risk. Own calculations.

Figure 5.6: Distribution of emotional skills by age and risk status



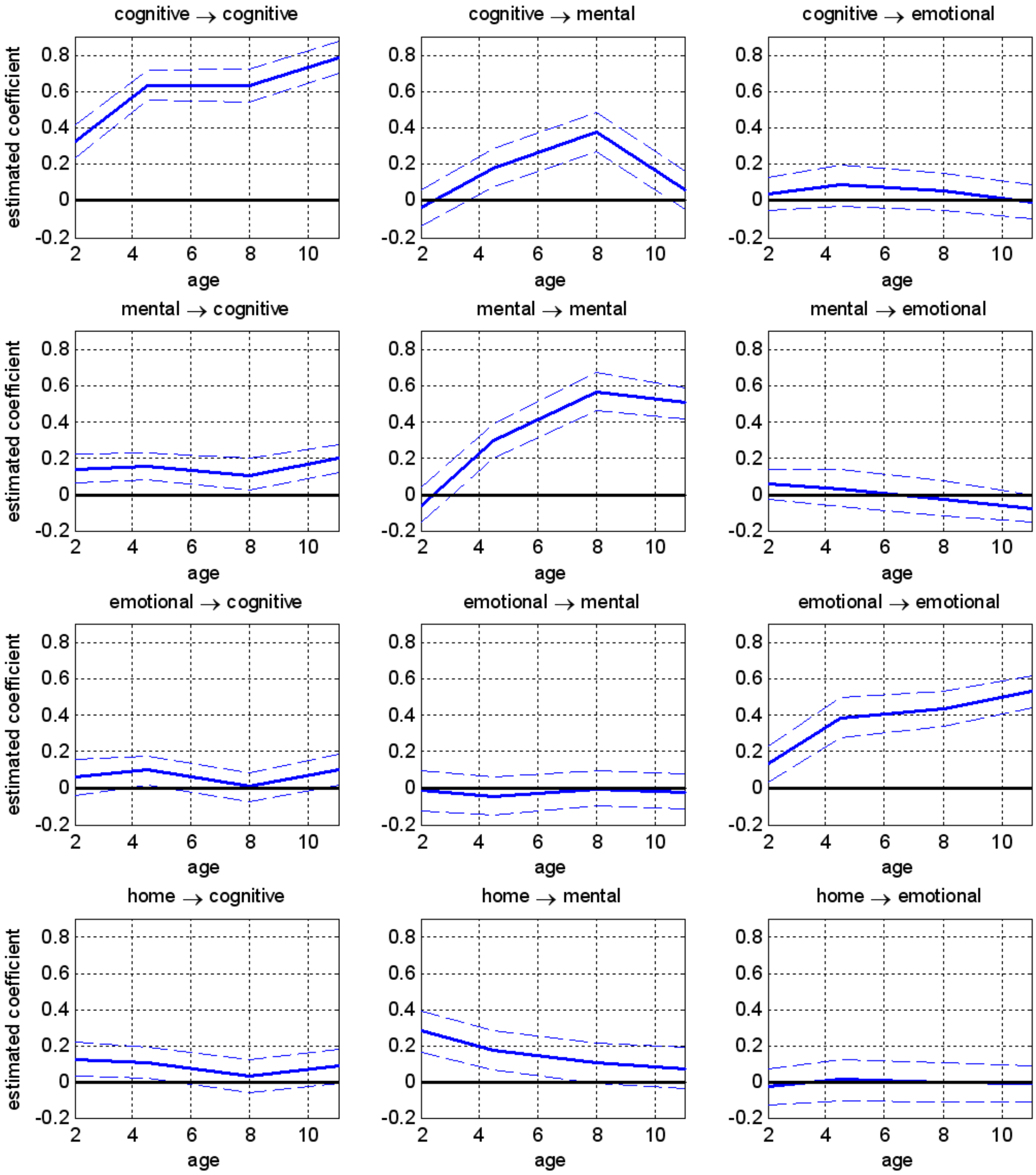
Note: Mean (and grey-shaded 95 % confidence bounds), the 10th, 90th percentile of standardized emotional skills.
Source: Mannheim Study of Children at Risk. Own calculations.

Figure 5.7: Distribution of parental investments by age and risk status



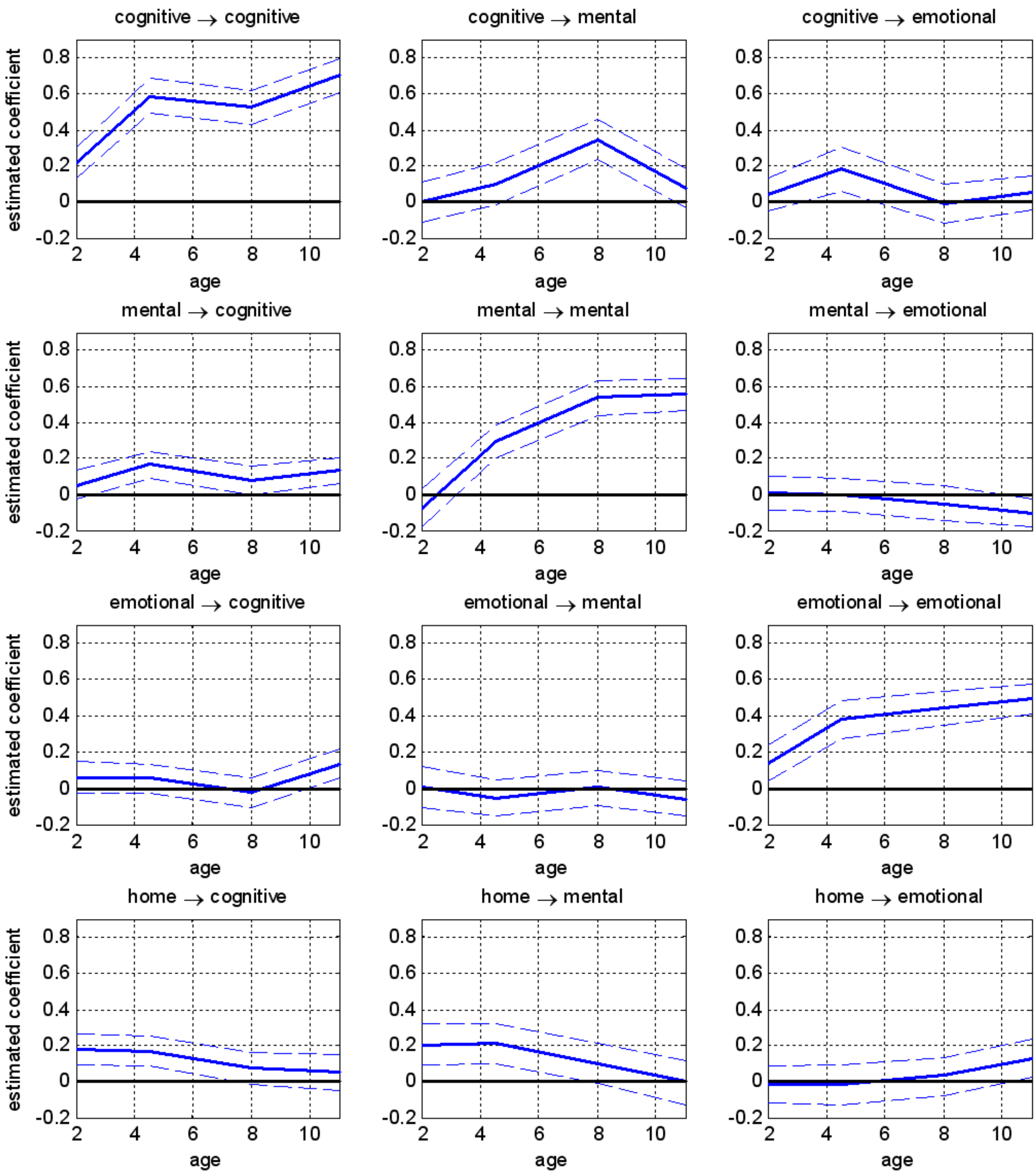
Note: Mean (and grey-shaded 95 % confidence bounds), the 10th, 90th percentile of standardized parental investments.
Source: Mannheim Study of Children at Risk. Own calculations.

Figure 5.8: Estimates of the skill production function with three skill factors



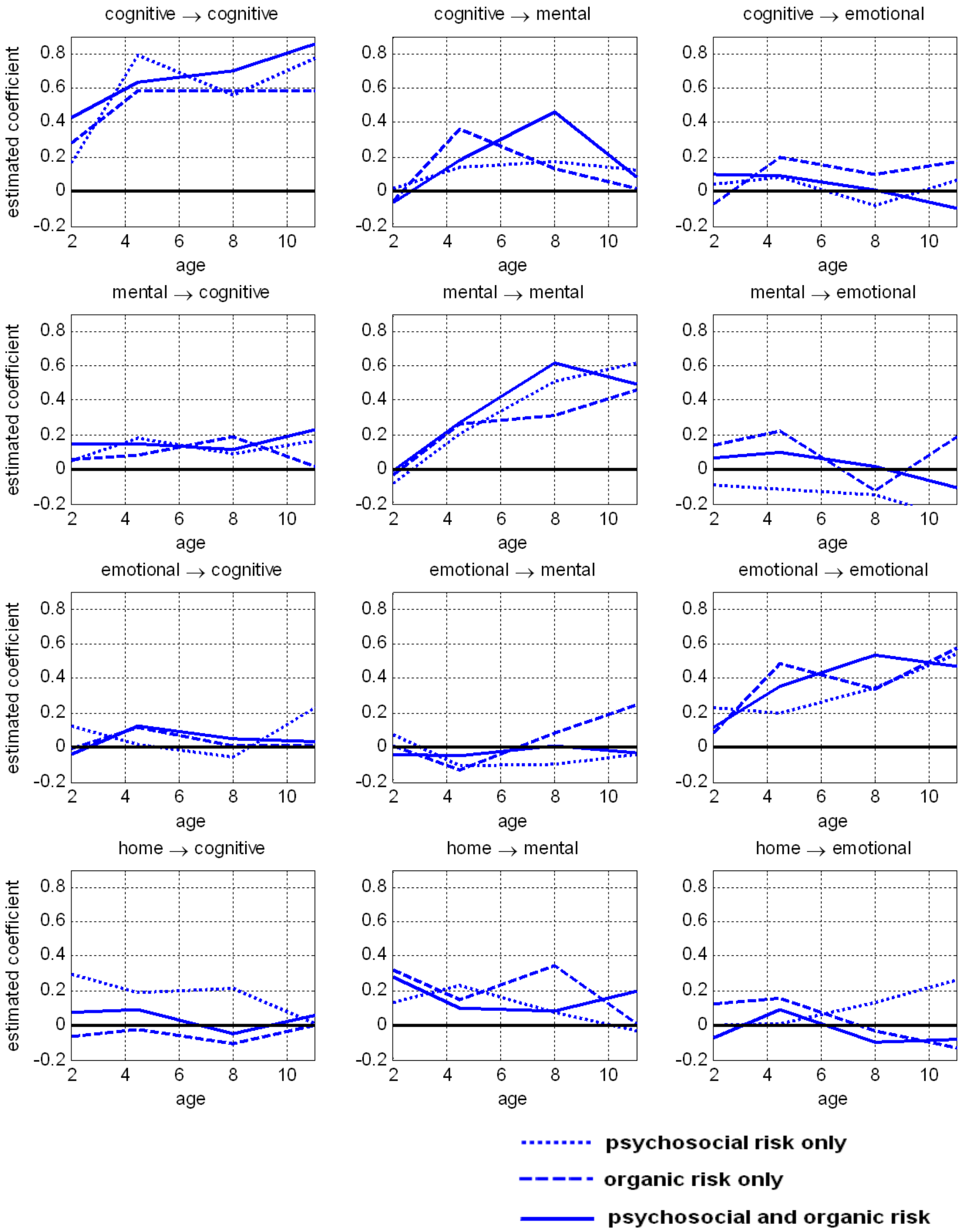
Note: 95 % confidence bounds are dashed lines (bootstrapped standard errors) 357 observations.
Source: Mannheim Study of Children at Risk. Own calculations.

Figure 5.9: (Weighted) estimates of the skill production function with three skill factors



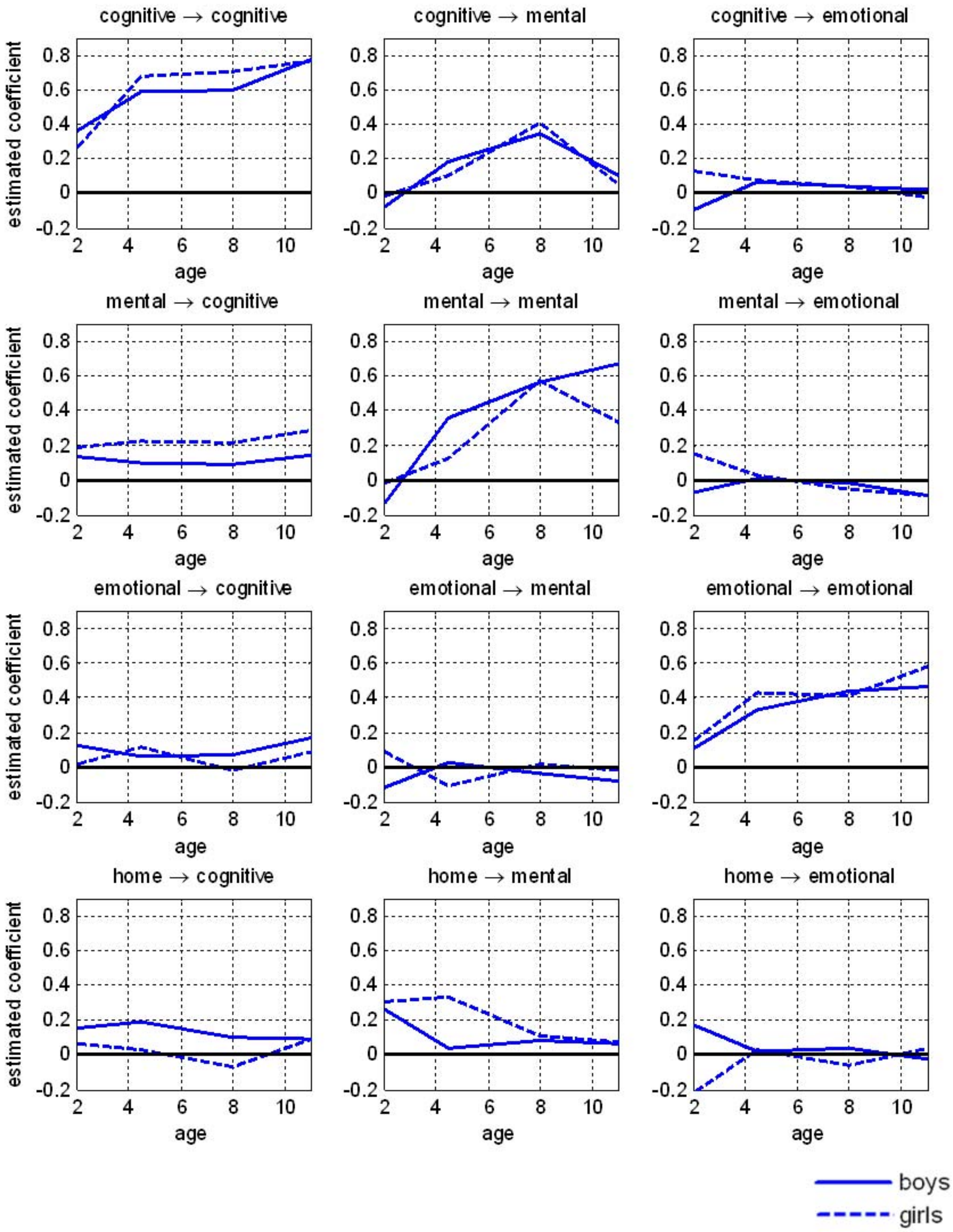
Note: 95 % confidence bounds are dashed lines (bootstrapped standard errors) 357 observations.
Source: Mannheim Study of Children at Risk. Own calculations.

Figure 5.10: Estimates of the skill production function with three skill factors by initial risk status



Note: 95 % confidence bounds are dashed lines (bootstrapped standard errors) 357 observations.
Source: Mannheim Study of Children at Risk. Own calculations.

Figure 5.11: Estimates of the skill production function with three skill factors by gender



Note: 95 % confidence bounds are dashed lines (bootstrapped standard errors) 357 observations.
Source: Mannheim Study of Children at Risk. Own calculations.

Tables:

Table 5.1: Correlations of skill measures with latent factors

age	IQ	MQ	NV-IQ	V-IQ	Activity	Ap-proach	Adapta-bility	Mood	Persis-tence
Cognitive Skills									
0.25	**0.92**	0.53			-0.07	0.18	0.08	0.15	0.07
2	**0.83**	0.61	0.63	0.60	0.10	0.18	0.13	0.21	0.23
4.5	**0.82**	0.62	0.61	0.77	0.09	0.09	0.18	0.13	0.38
8	**0.89**	0.45	0.64	0.61	0.04	0.01	0.18	0.01	0.38
11	**0.92**	0.52	0.41	0.70	0.05	-0.04	0.22	-0.12	0.32
Mental Skills									
0.25	-0.05	-0.09			0.66	-0.01	0.12	0.13	**0.83**
2	0.17	-0.08	0.12	0.18	**0.83**	-0.17	-0.02	0.13	**0.85**
4.5	0.20	0.18	0.18	0.22	**0.86**	-0.06	0.00	0.16	**0.84**
8	0.29	0.18	0.29	0.29	**0.85**	-0.06	0.24	0.11	**0.85**
11	0.13	0.11	0.32	0.20	**0.74**	-0.19	0.57	0.13	**0.82**
Emotional Skills									
0.25	0.20	0.10			0.05	**0.96**	0.61	0.69	0.29
2	0.20	0.24	0.15	0.22	0.06	**0.97**	0.57	**0.75**	0.08
4.5	0.12	0.20	0.05	0.14	0.04	**0.98**	**0.90**	**0.79**	0.16
8	0.07	0.05	0.08	0.06	0.09	**0.98**	**0.79**	**0.73**	0.11
11	-0.02	-0.01	-0.04	0.05	0.00	**0.96**	0.42	**0.78**	0.09

Source: Mannheim Study of Children at Risk. Own calculations.

Table 5.2: Identification of sensitive periods: Estimated difference of $b_t^k - b_{t+j}^k$

			unweighted model age in years			weighted model age in years		
			4.5	**8**	**11**	**4.5**	**8**	**11**
cognitive		**2**	0.02	**0.1***	0.04	0.01	**0.11***	**0.11***
	age	**4.5**		**0.08***	0.02		0.1	**0.11***
		8			-0.06			0.01
mental		**2**	0.11	**0.16***	**0.19***	-0.01	0.08	**0.16***
	age	**4.5**		0.07	**0.08***		0.1	**0.17***
		8			0.02			0.06
emotional		**2**	-0.04	-0.02	-0.03	0	-0.04	**-0.16***
	age	**4.5**		0.01	0		-0.04	**-0.17***
		8			-0.01			-0.13

Source: Mannheim Study of Children at Risk. 357 observations. Own calculations.
Note: Difference in coefficients is bootstrapped with 500 repetitions
* significant at 10% level

Table 5.3: Predicting school grades at the age of 11 and 15 years

stage (t)	cognitive skills	mental skills	emotional skills
3 months	**0.09***	0.05	0.06
	(0.03)	(0.03)	(0.03)
2 years	**0.19***	**0.11***	0.0
	(0.04)	(0.03)	(0.03)
4.5 years	**0.24***	**0.07***	0.0
	(0.04)	(0.03)	(0.03)
8 years	**0.25***	**0.14***	**0.07***
	(0.04)	(0.03)	(0.03)
11 years	**0.21***	**0.15***	**0.07***
	(0.04)	(0.03)	(0.03)

Source: Mannheim Study of Children at Risk. 357 observations. Own calculations.
Note: standard errors are in parentheses: *significant at 1% level; The dependent variable is an average over the six different grades at age 11 and 15. Mean = 4.07, min = 2.17, max = 5.95, with grades transformed to 1=fail, 2=insufficient, 3=fair, 4=satisfactory, 5=good, 6=excellent.

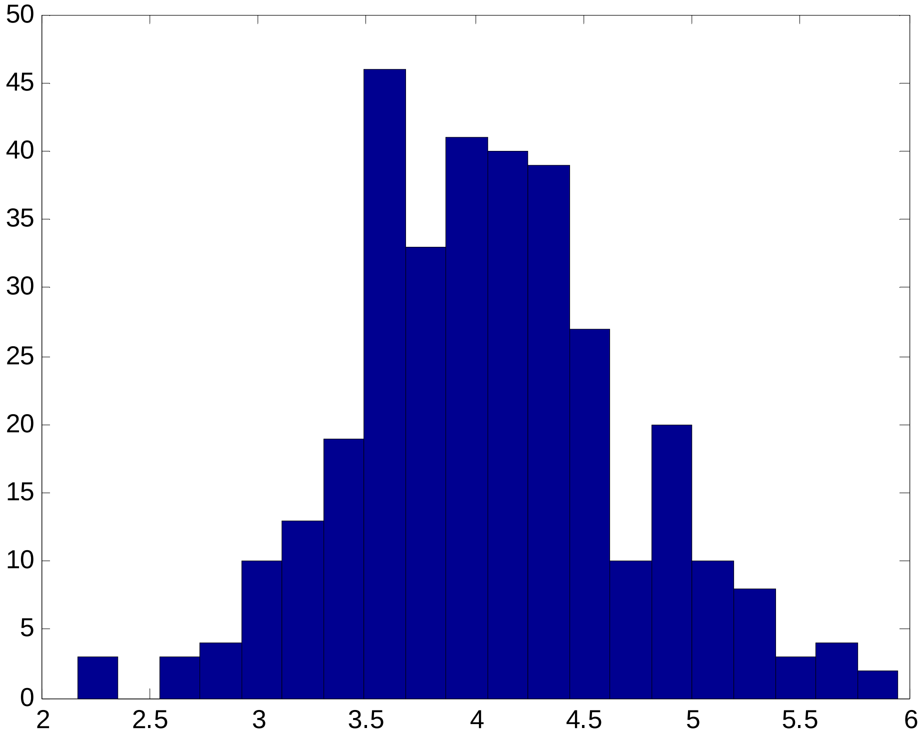
Table 5.4 Marginal Probability of attaining a high school degree

stage (t)	cognitive skills	mental skills	emotional skills
3 months	**0.07***	**0.07***	-0.03
	(0.02)	(0.02)	(0.02)
2 years	**0.13***	**0.10***	**-0.06****
	(0.03)	(0.03)	(0.02)
4.5 years	**0.18***	**0.14***	**-0.06***
	(0.03)	(0.02)	(0.02)
8 years	**0.18***	**0.14***	-0.001
	(0.03)	(0.02)	(0.02)
11 years	**0.18***	**0.17***	0.03
	(0.03)	(0.02)	(0.03)

Source: Mannheim Study of Children at Risk. 357 observations. Own calculations.
Note: standard errors are in parentheses: *significant at 1% level, ** significant at 5 % level. Share of children attending Gymnasium: 32.5%.

5.8 Appendix

Figure 5.1a: The distribution of school grades



Source: Mannheim Study of Children at Risk. 357 observations. Own calculations.

Table 5.1b: Sample weights

		Organic risk		
		low	medium	high
	low	0.35	0.32	0.11
Psycho-social risk	medium	0.36	0.41	0.11
	high	0.37	0.30	0.13

Source: Mannheim Study of Children at Risk. 357 observations. Own calculations.

Table 5.2b: Correlations of the skill measurements

	activity	approach	adaptability	mood	persistence	verbal IQ	Non-verbal IQ
MQ	0.31	0.20	0.41	0.28	0.46	0.51	0.65
activity		0.02	0.27	0.24	0.74	0.47	0.44
approach			0.73	0.75	0.07	0.22	0.20
adaptability				0.68	0.41	0.41	0.42
mood					0.30	0.32	0.26
persistence						0.67	0.69
verbal IQ							0.76

Source: Mannheim Study of Children at Risk. 357 observations. Own calculations.

Detailed description on the measurements of cognitive skills:

3 months: Cognitive abilities, *IQ*, were measured using the Mental Developmental Index (MDI) of the Bayley Scales of Infant Development (Bayley, 1969). The fine and gross motor abilities, *MQ* (called the motor quotient), were assessed by the Psychomotor Developmental Index (PDI) of the Bayley Scales.

2 years: The *IQ* was derived from the Mental Developmental Index (MDI) of the Bayley Scales of Infant Development. A differentiation is made between verbal abilities, *V-IQ*, and nonverbal cognitive abilities, *NV-IQ*. The verbal ability score is derived from the items of the Bayley Scales indicating language development, in combination with the expressive and the receptive language scales of the Münchener Funktionale Entwicklungsdiagnostik (MFED) (Köhler and Egelkraut, 1984). The nonverbal cognitive abilities are derived from the nonverbal items of the Bayley Scales, indicating basic, general abilities such as perception and logical and figural reasoning. The *MQ* was assessed by the Psychomotor Developmental Index (PDI) of the Bayley Scales.

4.5 years: The composite score of the *IQ* contained the Columbia Mental Maturity Scale (CMMS) (Burgmeister et al., 1972) and the subtest "sentence completion" of the Illinois Test of Psycholinguistic Abilities (ITPA), (Kirk et al., 1968; for the German version, see Angermaier, 1974). From these, a differentiation is made between *V-IQ*, language-dependent abilities and *NV-IQ*, indicating nonverbal abilities. The *MQ* was derived from the Test of Motor Abilities (MOT) 4-6 (Zimmer and Volkamer, 1984).

8 years: The composite score of the *IQ* was assessed by the Culture Fair Test (CFT) 1 (Weiss and Osterland, 1977), measuring nonverbal skills, such as the ability to perceive and integrate complex relationships in new situations, and the subtest “sentence completion” of the ITPA, mentioned above, indicating verbal reasoning (*V-IQ*). The *MQ* was assessed with the body coordination test for children (KTK) (Kiphard and Shilling, 1974).

11 years: The *IQ* was measured by the CFT 20 (Cattell, 1960) and a vocabulary test of the CFT 20, again allowing verbal, *V-IQ*, and nonverbal abilities, *NV-IQ*, to be distinguished. The MQ at age 11 years was assessed by means of a short version of the body coordination test for children (KTK).

6. Determinants of personality and skill development in the Socio-emotional environment during childhood

Abstract:

This study investigates the importance of different socio-economic conditions on skill formation by using German data from a longitudinal study, the Mannheim Study of Children at Risk, starting at birth. A rich set of psychometric variables regarding the socio-emotional environment from birth until late childhood is assessed. The paper extends previous approaches by splitting up the information on the environment into several dimensions. The results could help policy makers to design educational interventions. Birth risk and the early mother-child interaction are the most important determinants in infancy. In middle childhood cognitive skills can be enhanced by parents who stimulate child play with appropriate play materials and by parental support in learning numbers, shapes or letters. Personality rather tends to be linked to a harmonious and motivational parent-child relationship, in particular a positive emotional climate and the stimulation of independence. Early investments are the most important, but should be complemented by investments in late childhood to unfold their benefits.

Keywords: cognitive skills, personality, multidimensional investments, socio-emotional environment, childhood, partial least squares

JEL-classification: I12, I21, J13

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6.1 Introduction

In recent years several studies have examined the impact of environmental aspects on human capital formation (Borghans et al., 2008; Cunha and Heckman, 2009; Almond et al., 2009; Pfeiffer, 2010). They point out the shaping role of early childhood on skill formation and on socio-economic outcomes. An economic framework for analysing the relationships has been introduced by the technology of skill formation (Cunha and Heckman, 2007). Generally two major skill groups are distinguished: Cognitive skills including memory power, information processing speed, intellectual power, linguistic skills, motor skills as well as general problem solving abilities and noncognitive skills including motivation, persistence, activity level, social skills and emotional abilities, among others.

Even though most studies agree that the optimal timing of investments is in early childhood (Doyle et al., 2009), there is still much debate going on about how to optimally design investments. Heckman (2011) discusses different channels through which early intervention programs enhance noncognitive skills. The optimal assignments of private, governmental and non-governmental investment programs for different groups are analysed. Summing up skills and environmental aspects to a few aggregated scores might be tricky, because both are multidimensional. There may be many different ways to invest (e.g. material support vs. emotional support) and many different ways for individuals to profit from investments (e.g. in their discipline, mood or intellectual power). Understanding their interactions in more detail could help to better design investments and early intervention programs. Depending on the observed environment of each child at each age the lack of important investments could be monitored and remedied.

I use data from the Mannheim Study of Children at Risk (MARS), a longitudinal psychometric dataset following children from birth until early adulthood in Germany. The data is very rich in measurements of environmental conditions during early childhood as well as skills and socio-economic outcomes. A major part of environmental characteristics in the MARS is measured by the HOME score (Home Observation Measurement of the Environment, Bradly 1982), which assesses the parent-child interaction, living environment, play materials, activities and many other aspects by observations and interviews. The HOME consists of 25 to 101 items and 3 to 8 subscores, depending on age (for more details, see section 6.2).

The MARS data has been studied by Blomeyer et al. (2008, 2009), who look at particular measurements and find the measured abilities at preschool age as well as initial risk conditions at birth to be important for skills and performance later in life. Blomeyer et al. (2010) look at several selected environmental aspects of the HOME and the mother-child interaction and estimate the impact of early mother-child interaction on skill development until the age of 4.5 years. The mother-child interaction is as important as the early HOME for predicting the IQ in late childhood. Coneus et al. (2011) break up the skill dimension by using the complete information on eight different skill measurements to proxy three latent skills (cognitive, mental and emotional skills). In a second step the latent factors are used to estimate skill production functions. Mental and emotional skills are both noncognitive. The reason for the distinguishing two different noncognitive skills results from their great heterogeneity which can be illustrated with various statistical measures (cluster and factor analyses).

This paper combines the approach of Blomeyer et al. (2010) and Coneus et al. (2011) by splitting up the skill dimension and the environmental dimension simultaneously. The taxonomy of 3 different skill types introduced in Coneus et al. (2011) is adopted. The study extends previous approaches in three dimensions: Firstly, the HOME is split up into its aggregated subscores and into its single items. Secondly, the predictive power of additional variables of the environment (e.g. household composition, mother-child interaction, breasteeding, and childcare, among others) is examined. Thridly, a partial least squares regression (PLSR) is applied that is able to deal with the high number of correlated predictor variables.

Studies that estimate the effect of environmental aspects on skills have to consider a possible endogeneity bias. Two major sources of endogeneity are simultaneous causality and omitted variables. Not only investments could influence skills, but skills could also influence investments. A child that is smiling, motivated and curious might alter parental behaviour just like parental behaviour alters the child's personality (simultaneous causality). Several aspects might drive skill development, but are not observed such as genetic endowment, peers or the day care of grandparents (omitted variables).

I argue that simultaneous causality problems are small for several reasons. First, the correlation of the test result for one individual between interviewers amounts to 0.6 and 0.8 (Coneus et al., 2011). The respondent bias due to misunderstanding questionnaires is marginal, because the measures were commonly assessed by trained interviewers in different standardized surroundings. Also, the quality of the assessments is high, because trained interviewers observe children and their parents from birth on leading to a high data quality. In addition, the possible bias is reduced by only considering lagged environmental characteristics in the model.

Possible omitted variables are tried to be captured by integrating the largest possible number of explanatory and dependant variables in the model. Even though some aspects are not directly observed (e.g. care of grandparents) the data may contain variables that are related (e.g. number of persons in household, parental age).

The rest of the paper is organized as follows. Section 6.2 provides information about the data and variables and shows descriptive statistics. Section 6.3 addresses the estimation strategy. Section 6.4 presents the results, section 6.5 concludes.

6.2 Data and descriptive statistics

The study uses data from the Mannheim Study of Children at Risk (MARS), a longitudinal epidemiological cohort study following infants at risk from birth to adulthood. The initial sample contains 382 first-born children (184 boys, 198 girls), born between February 1986 and February 1988. Medical and psychological examinations elevating environmental aspects, skills, personality and social outcomes were assessed in different research waves. They took place when the children were 3 months, 2, 4.5, 8, 11, 15 and 18 years old and are still going on. Participation rates between the seven waves are high, despite the extensive survey procedure, comprising a large number of medical and psychological examinations. The sample at the age of 11 years amounts to 360 observations. For a more detailed description of the dataset see Blomeyer et al. (2008, 2009).

6.2.1 Environmental variables

Many aspects of the home environment of the children between the ages of 3 months to 11 years are captured by the HOME. Bradly and Caldwell (1980) found a strong link between cognitive abilities and the HOME as a relevant measure for preparing and fostering abilities starting in early childhood. This study uses a modified version of the original HOME that is assessed by parent interviews and direct observations. The composition of HOME items changes with age as other factors become relevant. It consists of 25 items at the age of three months, 87 at the age of 2 years, 95 at the age of 4.5 years and 59 items at the ages of 8 years. The number of HOME items used at the age of 2 and 4.5 years is extended compared to previous studies (Blomeyer et al., 2009; Coneus et al., 2011), who used 29 and 38 items at the ages of 2 and 4.5 years and Blomeyer et al. (2010), who used a selection of 40 and 47 items at the ages of 2 and 4.5 years[32]. Items are grouped into subscores, as table 6.1 shows.

Table 6.1: Description oft he HOME subscores and items

Subscore	Description	Items	Age when measured
Mother-child Interaction	Reactivity of the mother towards child, vocalisation, smooching, avoidance of punishment and aggression, integration of child during interview	11	3 months
Living Environment	Play materials, security, nursery, apartment appearance, yard quality, pet, etc…	6 (3 months) 20 (2-4.5 years)	3 months 2 years 4.5 years
Conversation process with parents and child	Clear speech, language, interest in interview, praising child, honesty, etc…	8	3 months 2 years 4.5 years
Stimulation of development and language	Allowance of child play, speech quality towards child, media use, types of playing (songs, colors, numbers, letters, etc...)	13	2 years 4.5 years
Avoidance of Restriction and Punishment	Allowing child to play during housework, avoidance of punishment, interesting activities for child during housework/interview	7	2 years 4.5 years
Promotion of Maturation and Autonomy	Praising child, promotion of autonomy with reasonable constraints, learning to tie shoes, to dress, to tidy up, to be polite, etc...	12	2 years 4.5 years
Play Materials	Toys to drive, to paint, to read, to build, to cuddle, to play music, to puzzle, to learn colors, numbers etc…	13 (2 years) 16 (4.5 years)	2 years 4.5 years
Emotional Climate	Integration of child during interview, smooching, avoidance of punishment and aggression, praising child, motivating the child, compassion	18 (2-4.5 years) 8 (8 years)	2 years 4.5 years 8 years
Emotional and Verbal Responsivity	Clear daily routine, praising child, motivating child, integration and support of child during interview, use of full sentences	10	8 years
Promotion of Social Maturity	Expecting child to tidy up, help in the household, to do homework, reasonable rules, consistency	6	8 years
Experiences and Materials promoting development	Radio and cassette recorder, music instruments, books, dictionaries, newspapers, visits to/from friends, etc…	8	8 years
Active Stimulation	Reasonable TV use, hobbies, variety of leisure activities, playground use, library card, museum visits, trips and travelling	8	8 years
Paternal engagement	Father (or equivalent person) engages in outdoor activities, sees child at least 4 days a week, participates at meals, etc…	4	8 years
Material environment	Appearance of house/apartment, order and cleanness, sufficient living space per person, acceptable noise level, secure environment for child, no smoking	7	8 years
Activities promoting development	Visits to friends or relatives, taking child to concerts, theatre, business trips, travelling, bike riding, roller skating, etc…	6	8 years

[32] Blomeyer et al. (2011) adjusted the selection in a way that it matches the original HOME as well as possible. In this study, however, all items are used for two reasons. Firstly, to address the problems of omitted variables as well as possible and secondly, because the estimator introduced in section 3 is robust to additional explanatory variables.

A major goal of this paper is to assess the predictive power of additional environmental variables. During the HOME interviews a general ***interviewer rating of the contact person*** was carried out at the ages from 3 months to 4.5 years at a 5-point scale rating. Elaborated aspects include the "perceived honesty" of the contact person during the interview varying from "continuously artificial" to "continuously sincere", the "acceptance of the child" during the interview varying from "not accepting child during the whole interview" to "child continuously accepted" and "parental reactivity "varying from "not reactive at all towards child" to "completely reactive towards child".

Additional variables on environmental aspects of the earliest stages of life are birth risks. A rating of organic risk was conducted based on the information of the maternal obstetrical and infant neonatal record. It is measured by the psychological and medical rating of several pre-, peri- or neonatal complications including premature birth, the EPH-gestosis of the mother, low birth weight, asphyxia, seizures, respiratory therapy, sepsis, etc. The variable "***low organic risk"*** denotes to the absence of organic risk factors. A rating of psychosocial risk was made based on the risk index developed by Rutter and Quinton (1977). It includes parental psychiatric disorders, broken home, delinquency, early parenthood, low quality partnership, unwanted pregnancy, disease and unemployment. "***Low psychosocial risk"*** denotes to the absence of psychosocial risk factors.

At the age of 3 months video-taped information on the ***mother-child interaction*** was rated by the MBS-MKI-S scale (Mannheimer Beurteilungsskala zur Erfassung der Mutter-Kind-Interaktion im Säuglingsalter, see Esser er al., 1989). Maternal behavior is broken down into eight dimensions: Emotion, tenderness, verbalization, verbal restrictions, congruity/authenticity, variability, reactivity/sensitivity and stimulation. Infant behavior is broken down into five dimensions: Emotion/facial expressions, verbalization, viewing direction, reactivity and the potential willingness to interact.

Another question this study will address is if the ***duration of breastfeeding*** provides additional predictive power on future skills. It was surveyed by an interview of the mothers at the age of 2 years and ranges from 0 to 104 weeks. It is split up into two variables in this paper: The amount of breastfeeding until the age of 3 month and the amount of breastfeeding until the age of 2 years.

Children do not only stay at home, especially during late childhood. For this reason, I also include the quality of ***neighborhood environment.*** It was assessed together with the HOME score at all ages between 3 months and 11 years**.** The house conditions in the neighborhood, the house type, the infrastructure quality as well as nearby disturbances of traffic, noise, industry and bars were rated.

The data contain information on several characterstics of the parents. ***Parental education*** at the age of 3 months describes the highest graduation of the mother and father. Further variables include the ***income per capita, parental age,*** the ***number of persons in the household*** and ***single parenthood.*** Single parenthood is also part of psychosocial risk. It is separately included as psychosocial risk refers to the conditions before and during birth, but single parenthood was assessed in all waves. Information about ***external childcare*** at the age of 4.5 years was assessed retrospectively in an interview. A score that includes information on the institutional childcare of the last 6, 12 and 18 months (in daily and weekly dimensions), kindergarten use and nanny care is generated.

6.2.2 Skill variables

The most prominent skill variable is the ***IQ*** (intelligence quotient) that measures cognitive abilities. It was assessed by the Mental Developmental Index (MDI) of the Bayley Scales of Infant Development (Bayley, 1969) at the ages of 3 months and 2 years, the Columbia Mental Maturity Scale (CMMS, Burgemeister et al., 1972) at the age of 4.5 years and the Culture Fair Test at the ages of 8 and 11 years (Cattell, 1960). Each test consists of a variety of subtests such as numeracy, memory, receptive and expressive language skills. The *IQ* was measured in a verbal ***(verbal IQ)*** as well as in a nonverbal dimension ***(nonverbal IQ)*** from the age of two years onwards.

The ***MQ*** (motor quotient) was assessed by the Psychomotor Developmental Index (PDI) of the Bayley Scales at the ages of 3 months and 2 years, the Test of Motor Abilities (MOT) 4-6 (Zimmer and Volkamer, 1984) at the age of 4.5 years and the Body coordination test for children (KTK) (Kiphard and Shilling, 1974). The MQ often relates to the IQ. For more detailed information on measuring the IQ and the MQ in the MARS, see Bloymeyer et al. (2009).

Evidence suggests that noncognitive skills are at least equally important (Duckworth et al. 2005). Besides the cognitive measures the data contain several personality traits that capture noncognitive abilities. They were surveyed within a standardized parent-interview and during structured direct observations in four standardized settings on two different days in both familiar (home) and unfamiliar (laboratory) surroundings. All ratings were assessed by trained judges on 5-point rating scales of five temperamental dimensions adapted from the New York Longitudinal Study NYLS

(Thomas et al., 1968). Personality taxonomies are usually based on parent interviews and direct observations instead of questionnaires like alternative personality measures such as the Big Five. The eight personality measures employed in this study are as follows: ***Activity*** describes the frequency and intensity of motor behaviour ranging from "being inactive and slow" to "being overactive and restless". ***Approach*** describes the initial reaction to new stimuli (e.g. strangers, new food, or unfamiliar surroundings) ranging from "withdrawal" to "approach". ***Adaptability*** denotes the length of time that is needed to get habituated to the new stimuli going from "very slow/not at all adapting" to "very quickly adapting". ***Mood*** describes the general tendency of the child to be in good or bad temper ranging from "negative mood" to "positive mood". ***Persistence*** refers to a child's ability to pursue a particular activity and its continuation in the face of obstacles varying from "very low" to "very high". ***Reactivity*** measures the vehemence of the child's expression of positive and negative emotions ranging from "apathetic" to "irritable/boisterous". ***Rhythmicity*** refers to the regularity of biological functions (e.g. sleep-wake-cycle, hunger, etc.) ranging from "unpredictable" to "totally regular (like clockwork"). Finally, ***responsiveness*** accounts for the sensitivity in the child's reaction to environmental changes or external stimuli (e.g. pain, parental frowning, food temperature or new food) going from "oversensitive" to "very insensitive".[33] For more detailed information on the skill measures see Coneus et al. (2011) and Blomeyer et al. (2011).

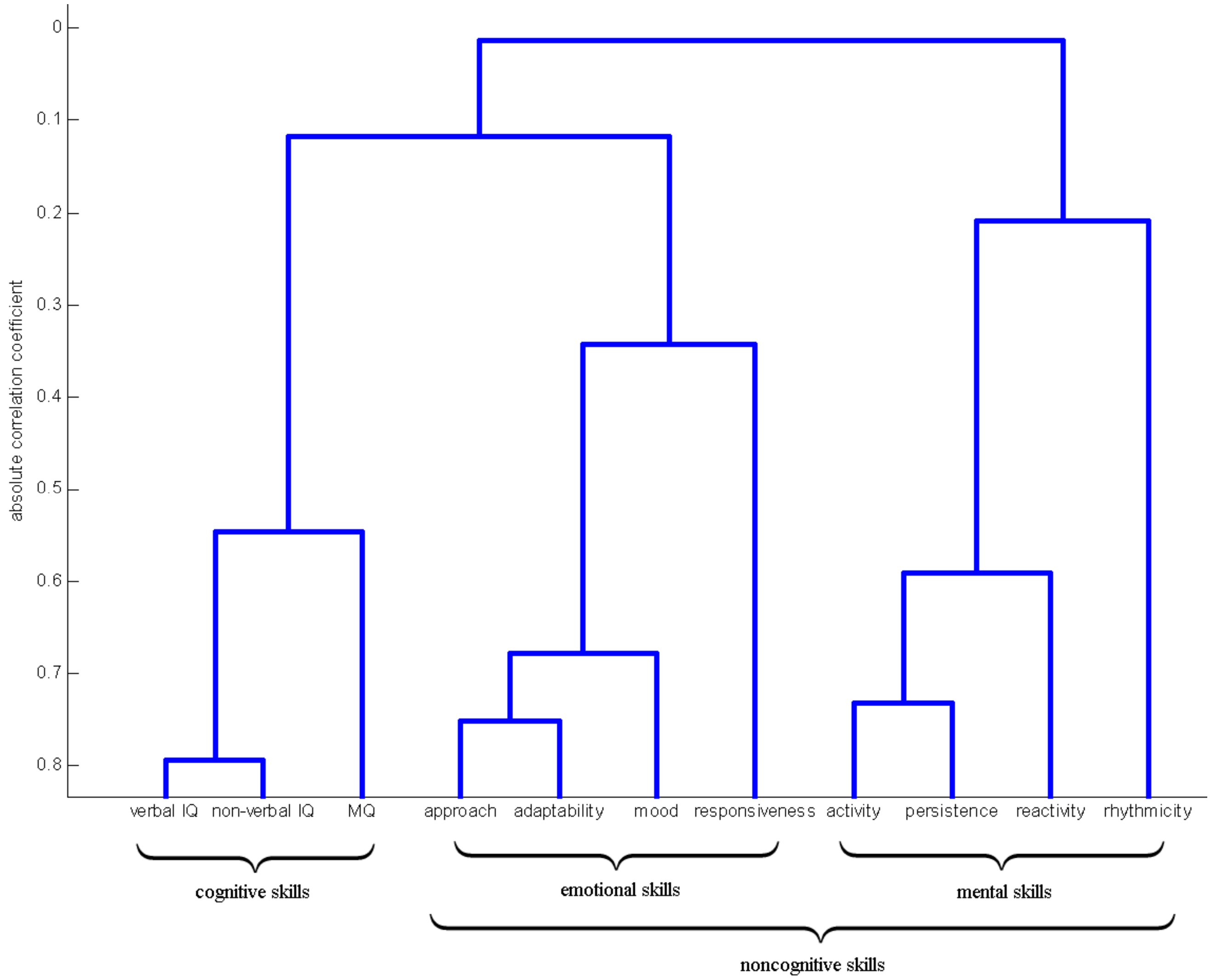
To obtain an overview of how the skills and personality measures (noncognitive skills) are related I apply hierarchical clustering (see figure 1). First, the absolute correlations are calculated and the pairs with the highest correlations are grouped. Next, the pairs that are in close proximity are linked using the information generated in the first step. As objects are paired into binary clusters, the newly formed clusters are grouped into larger clusters until a hierarchical tree is formed (Coneus et al., 2011). The link where groups in the tree presented in figure 1 connect always refers to the smallest correlation to the next cluster, e.g. the smallest absolute correlation between the measurement groups "IQ, MQ" and "approach, adaptability, mood, responsiveness" is 0.12. The Y-axis shows the absolute correlation, the X-axis the different skill measurements. Figure 6.1 shows that three major clusters exist: cognitive skills, mental skills and emotional skills. The cognitive group consists of the IQ (verbal IQ and nonverbal IQ) and the MQ. The emotional group consists of approach, adaptability and mood. All emotional measures are at least correlated by 0.67. Responsive-

[33] Usually high ratings can be associated with high noncognitive skills. In the case of activity, reactivity and sensitivity however the medium rating "3" is optimal. Hyperactivity, boisterous and very insensitive behavior can involve problems. Hence, those three temperamental measures are transformed such that the medium ratings come along with the highest score, "5", whereas the very high and very low ratings come along with the lowest score, "1".

ness is more distinct (its correlation with adaptability is 0.43). The mental group consists of activity, persistence and reactivity all being correlated by at least 0.61. Rhythmicity is only distantly related to the mental skill group. The results can be confirmed with a factor analysis (see Coneus et al., 2011).

To sum up, ***cognitive skills*** refer to memory power, information processing speed, intellectual power, linguistic skills and motor skills. ***Emotional skills*** describe the mood and the reaction and abilities to cope with new stimuli. ***Mental skills*** eventually refer to the ability to pursue certain goals and a reasonable activity level.

Figure 6.1: Correlations and clustering of skill measures



6.2.3 Variables on social outcomes

Skills generally lead to social achievements (see Pfeiffer and Reuß, 2008). Social outcomes give a glimpse on how individuals might perform later in life and on the labour market. In this study the child functional levels at the age of 11 years are studied. The functional level is a 7-point scale that condenses a multiplicity of social outcomes of the child (Marcus et al., 1993). It is broken down into five dimensions: The ***"functional level in the family"*** measures the role of the child in the family ranging on from "disintegrated, destructive behavior" to "positive engagement that improves the family environment". The ***"functional level in school"*** describes the child's achievements at school going from "huge problems at school/in attaining reading and math skills" to "very successful, high school outcomes, barely challenged". The quality of peer relations is described by the "***peer-functional level"*** from "unable to develop peer contacts" vs. "very popular, many peers, leading position" The ***"functional level of interests and leisure"*** ranges from "no interests, never inspired" to "multiple interests, high achievement in several leisure activities". Finally, the ***"functional level of autonomy"*** measures the level of independence on a scale from "dependent, not able to be out of home without assistance" to "able to travel alone, very autonomous".

6.3 Method

6.3.1 Estimation strategy

The major goal of this study is to examine the predictive power different kinds of investments have on future skills. For this purpose, the technology of skill formation is employed (Cunha and Heckman, 2007):

$$S_t^c = f_t(S_{t-1}^c, S_{t-1}^m, S_{t-1}^e, E_{t-1}) \quad (6.1)$$

S_t^c, S_t^m and S_t^e denote cognitive, mental and emotional skills in period *t* and E_{t-1} denotes the environmental conditions that can be interpreted as investments in the child's skills for each period *t.* I try to reduce possible problems of simultaneous causality by only inserting lagged environmental aspects into equation 6.2.

In order to decrease the omitted variable bias as much as possible, all of the 11 skill variables and all of the measured environmental aspects (in some waves more than 100 items) are integrated in the model. To do so, a large set of predictor variables (environmental aspects) is regressed on the relevant response variables (skills and social outcomes). Using many correlated explanatory variables in traditional ordinary least squares regression is likely to cause multicollinearity problems (Wooldridge, 2003). It often makes the original regressor matrix almost singular and leads to identification problems. To overcome this problem several techniques have been developed such as ridge regression (Hoerl and Kennard, 1970). In ridge regression the matrix of the original regressors is modified such that it remains non-singular. For the application of this technique, however, a lot of computation is required if the number of variables is large (Aswani and Bickel, 2011). Alternatively one could implement principal component or factor analysis (Jöreskog, 1967; Cunha et al., 2010; Coneus et al., 2011). Those techniques aim at generating a small number of principal components (or latent factors) that comprise as much variation of the original variables as possible. As they can be restricted to be orthogonal in the regression, multicollinearity problems are eliminated even though a lot of information is preserved.

While factor analysis and principal component regression (PCR) are useful tools to reduce the multiplicity of response variables, their application involves some problems if one aims at reducing the multiplicity of inputs of predictor variables. Ideally the latent factors of the predictor variables should be chosen by taking into account how well they are able to predict the response variables. Choosing them independently from their responses could lead to an over-specification of the model. Additional latent predictor scores might produce unnecessary bias. Considering the principle that "it can scarcely be denied that the supreme goal of all theory is to make the irreducible basic elements as simple and as few as possible without having to surrender the adequate representation of a single datum of experience" (Einstein, 1934), the selection of latent predictor scores should lead to a model as precise as necessary but as simple and parsimonious as possible.

A regression technique suited to deal with numerous correlated predictor variables is partial least squares regression (PLSR). Aswani and Bickel (2011) perform predictions from highly correlated variables and find PLSR to perform significantly better than PCR and ridge regession. Wold (1966) did a pioneering work on PLSR in the field of econometrics. Since then PLSR has been popular among chemometricians and chemical engineers (Helland, 1980; Wold et al. 2001), but has also been used in economics (Dijkstra, 1983; Knight, 2008).

The basic framework of PLSR in this paper consists of an n-by-q matrix S of q skills and n observations and an n-by-p matrix E with p environmental aspects. To regress skill variables in S on the environment E, PLSR tries to find latent factors that play the same role as E (Rao et al., 2008; Boulesteix and Strimmer, 2007). The basic framework of PLS consists of two equations 6.2 and 6.3:

$$E = TP^T + \varepsilon_E \tag{6.2}$$

$$S = TQ^T + \varepsilon_S \tag{6.3}$$

T is an n-by-c matrix giving c latent components for n observations, P is a p-by-c matrix and Q a q-by-c matrix of coefficients. ε_E and ε_S contain the random errors. In a first step all variables are standardized to a mean value of 0 and a variance of 1 as uncentered basic data is assumed (Rao et al., 2008). Before starting with the identification, c has to be specified exogenously. Each latent factor is a linear combination of $E_1,\ldots,E_p$:

$$T = EW \tag{6.4}$$

W is a p-by-c matrix of weights. The aim of PLSR is to capture as much information of E as possible in order to predict $S_1,\ldots,S_q$ while reducing the dimensionality of the regression problem by using fewer components than p. In this paper W is identified by the SIMPLS algorithm (for a detailed description, see de Jong, 1993). In SIMPLS the following maximization is solved for each w_i in W with i=1,...,c:

$$w_i = \arg\max_w w^T E^T SS^T Ew \tag{6.5}$$

subject to

$w_i^T w_i = 1$ and $t_i^T t_j = w_i^T E^T E w_j = 0$ for $j = 1,\ldots,i-1$.

If we assume q>1 the term on the right hand side of equation 6.5 is the sum of the squared empirical covariances between the latent environmental factors, T, and the measured skills, $S_1,\ldots,S_q$:

$$w^T E^T SS^T Ew = ((Ew)^T S)^T ((Ew)^T S) = n^2 \cdot \sum_{j=1}^{q} Cov(T, S_j)^2 \,. \tag{6.6}$$

After identifying W, the latent components can be computed using equation 6.4. Those are then used for prediction in place of the original environmental variables. Q^T is obtained as the least squares solution of (6.2):

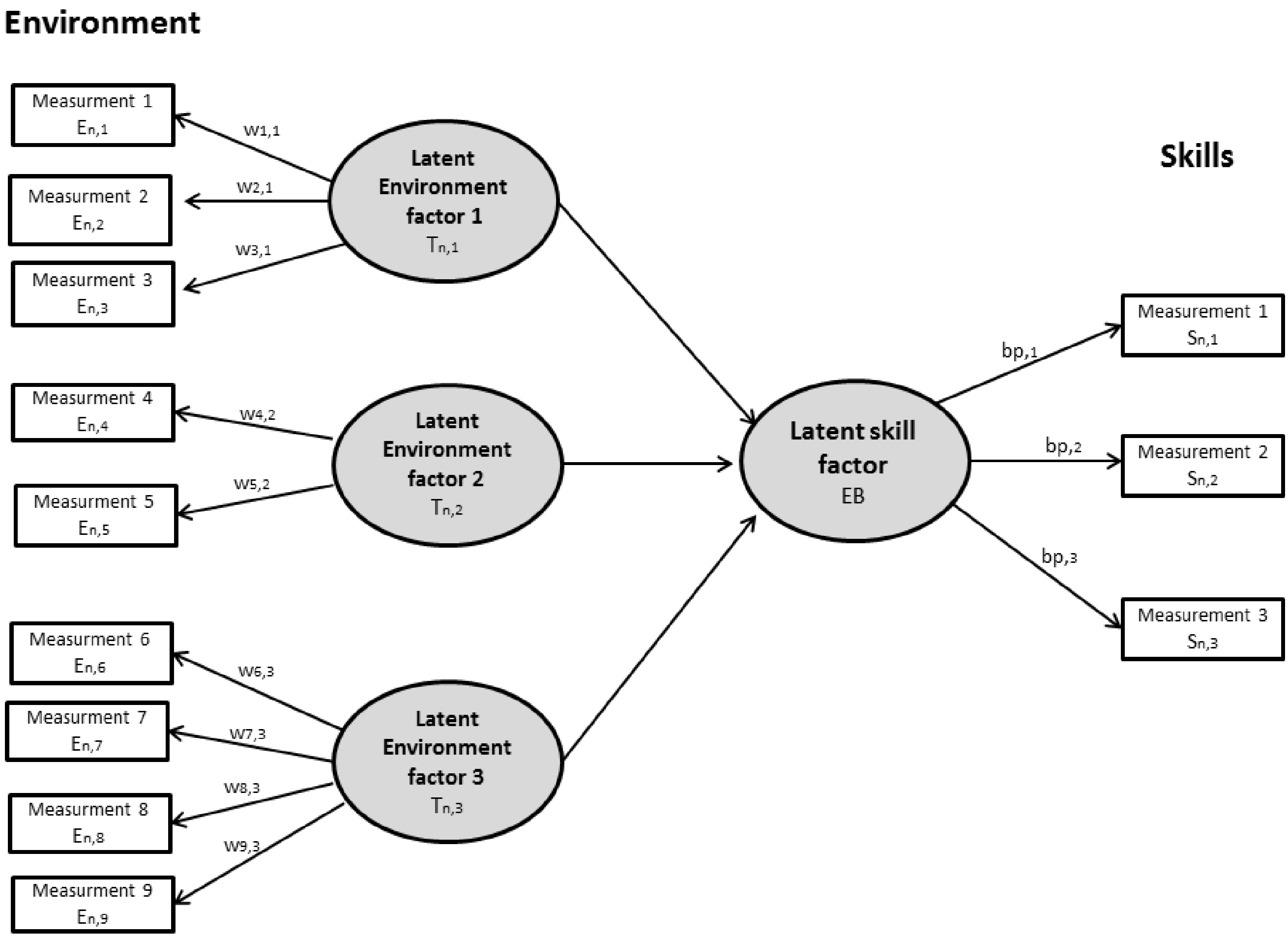
$$Q^T = (T^T T)^{-1} T^T Y \tag{6.7}$$

Obtaining P^T is analogous. Finally the *p*-by-*q* matrix B of regression coefficients for the model S=EB+ε_S is given as:

$$B = WQ^T \tag{6.8}$$

Figure 6.2 illustrates the principles of PLSR for *c*=3, q=3 and p=9. For simplification only some of the w and the corresponding arrows are shown.

Figure 6.2: Example of partial least squares regression



PLSR offers several advantages. If $n \leq p$, traditional regression techniques such al OLS cannot be applied because the p-by-p covariance matrix E^TE is singular. In contrast, PLSR may be applied (Garthwaite, 1994). The precision and reliability of PLSR can be increased by either increasing n or p or even both. As the number of 382 observations in the first period is relatively low compared to other data while the number of variables is relatively high, this is a useful feature. By performing Monte Carlo simulations, Cassel et al. (1999) show PLSR to be robust with regard to skewness, multicollinearity, misspecification and that the latent variable scores conform to the true values. For these reasons PLSR can come in operation with quasi-metric (e.g. Likert-scales, see Vinzi et al., 2009), metric or dichotomous data. This is advantageous when analyzing MARS as different skills and environmental aspects are measured on different scales with different ratings.

The interpretation of the PLSR coefficients may be difficult as the causal relationship is only estimated for the latent factors. In case of many omitted variables the significant coefficients have to be interpreted as predictors and signals of underlying latent factors that may have causal relationships. The reliablitiy of the coefficients increases with the inclusion of additional variables into the model.

To estimate the technology of skill formation specified in equation 6.1. In line with Coneus et al. (2011) I restrict the number latent skill factors to 3. The resulting factors $\hat{S}$ correspond to cognitive, mental and emotional skills. For the age of 3 month (0.25 years) the technology of skill formation is estimated by a PLSR with

$$S^{0.25} = \begin{pmatrix} s_{1,1}^{0.25} & \cdots & s_{1,q}^{0.25} \\ \vdots & \ddots & \vdots \\ s_{n,1}^{0.25} & \cdots & s_{n,q}^{0.25} \end{pmatrix}. \tag{6.9}$$

$s_{1,1}^{0.25}$ describes the first measured skill for the first individual at the age of 0.25 years, $s_{n,1}^{0.25}$ is the first measured skill for the n^th^ individual and $s_{1,q}^{0.25}$ the q^th^ measured skill for the first individual. E for each period consists of the environmental aspects $e_{i,j}$. Only lagged aspects $e_{i,j}^{t-1}$ are considered. That means for estimating skills at the age of 3 months, $E^{0.25}$ includes only the birth risks (age 0) and a few parental characteristics.

$$E^{0.25} = \begin{pmatrix} e^{0}_{1,1} & \cdots & e^{0}_{1,p} \\ \vdots & \ddots & \vdots \\ e^{0}_{n,1} & \cdots & e^{0}_{n,p} \end{pmatrix} \tag{6.10}$$

For the ages of t=2, 4.5, 8 and 11 years E is extended by the three latent skill factors k=3 of the previous period, $\hat{S}^{t-1}_{n,k}$.

$$S^{t} = \begin{pmatrix} s^{t}_{1,1} & \cdots & s^{t}_{1,q} \\ \vdots & \ddots & \vdots \\ s^{t}_{n,1} & \cdots & s^{t}_{n,q} \end{pmatrix} \tag{6.11}$$

and

$$E^{t} = \begin{pmatrix} e^{t-1}_{1,1} & \cdots & e^{t-1}_{1,p-3} & \hat{S}^{t-1}_{1,emotional} & \hat{S}^{t-1}_{1,cognitive} & \hat{S}^{t-1}_{1,mental} \\ \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ e^{t-1}_{n,1} & \cdots & e^{t-1}_{n,p-3} & \hat{S}^{t-1}_{n,emotional} & \hat{S}^{t-1}_{n,cognitive} & \hat{S}^{t-1}_{n,mental} \end{pmatrix} \tag{6.12}$$

The model is then estimated according to (2) - (8).

Before starting the estimation, the number of latent components c needs to be specified. With each additional component c the fraction of variance explained in S is increased, but a too large number of components might lead to overfitting. For $\lim_{c \to p} B$ the coefficients of PLSR become similar to OLS involving possible problems of multicollinearity. Hence, c should be sufficiently large to capture enough variation of S, but as small as possible. A useful tool for finding the optimal number of components is the value of c that minimizes the root-mean-square error of cross-validation (RMSECV), which is a measure of a model's ability to predict new samples (Rao et. al., 2008):

$$RMSECV_{c} = \sqrt{\frac{\sum_{i=1}^{n} (s_{c,i} - \widetilde{s_{c,i}})^{2}}{n}} \tag{6.13}$$

Given a specific number of latent components c, $s_{c,i}$ are the predicted skills of the sample included in the model formation and $\widetilde{s_{c,i}}$ are predictions for samples not included in the model formation. For the purpose of cross validation I partition the total sample into 10 subsamples. As the standard errors in PLSR cannot be derived directly from the formal structure, bootstrapping with 10,000 repetitions is used.

6.3.2 Method Illustration

Suppose we want to estimate a simplified specification of the technology of skill formation for the IQ at the age of 8 years:

$$S_8^c = f_8(S_{4.5}^c, I_{4.5}) \qquad (6.14)$$

S^c in equation 6.14 is assumed to be solely measured by the IQ[34]. Assume $I_{4.5}$ to contain multiple environmental aspects at the age of 4.5 years, including the HOME subscores and others (see table 6.1 and table 6.2). Some of those variables are correlated by more than 0.6, e.g. the correlation of "avoidance of punishment and restriction" and "emotional climate" is 0.62. The results for estimations with OLS, PCR and PLSR are presented in table 6.2.

The first column (1) shows the OLS regression for the previous period IQ and the aggregated HOME. This resembles studies estimating the technology of skill formation for the MARS (Blomeyer et al., 2009; Coneus et al., 2011) with the difference that noncognitive skills are missing in equation 6.14. The self-productivity is estimated with a coefficient of 0.83. The coefficient of the HOME score at the age of 4.5 years is 0.19 and significant. An increase in the HOME at the age of 4.5 years by 0.19 standard deviations (which, for example, corresponds to an increase of the 40th to the 89th percentile in the HOME distribution) leads to an increase of the IQ at the age of 8 years by 2.85 points[35]. The second column (2) shows the OLS regression for the case when the HOME is split up into 7 different subscores and several additional environmental variables are added. Several coefficients are significant and positive, such as "play materials", the parental age, living with biological parents and the number of persons in the household, while others such as "stimulation of development and language", "single parenthood" and "external childcare" are negative. Some of the results seem counterintuitive. They might result from the high correlations among predictors. Column (3) presents the results for principal component regression.

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[34] In the rest oft he paper it is assumed the cognitive skills are additionally measured by the verbal IQ, nonverbal IQ and the MQ.

[35] The IQ scale is normalized to a mean of 100 and a standard deviation of 15. Hence the coefficient values simply can be multiplied by 15 to see the gain in IQ points (0.19*15=2.85)

Table 6.2: Estimation of the IQ at the age of 8 years by OLS, PCR and PLSR

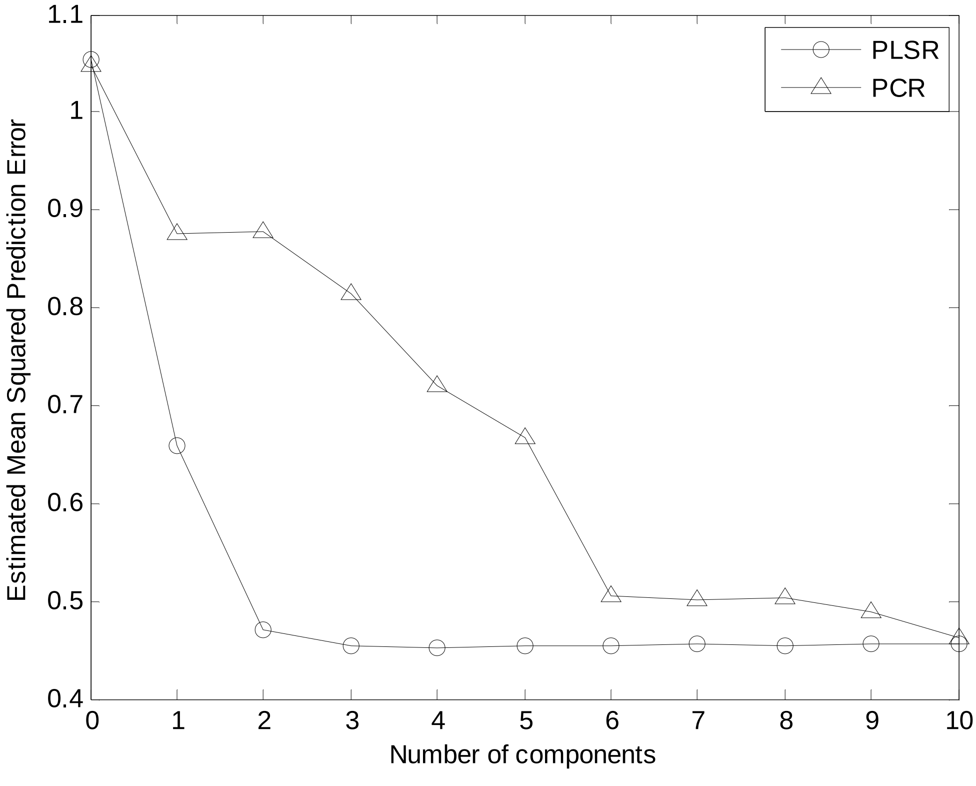
	(1) OLS		(2) OLS		(3) PCR		(4) PLSR	
HOME SCORE (total)	**0.19 *****	(.065)						
Interviewer rating of contact person			0.02	(.041)	-0.06	(.079)	-0.05	(.035)
HOME: Conversation process with parents			0	(.05)	0.05	(.088)	0.03	(.037)
HOME: Stimulation of development and language			**-0.10 ****	(.049)	0	(.061)	-0.05	(.036)
HOME: Living Environment			-0.04	(.051)	0.07	(.086)	0.02	(.041)
HOME: Avoidance and Restriction and Punishment			0.1	(.065)	0.05	(.047)	**0.05 ***	(.03)
HOME: Emotional Climate			0.05	(.071)	0.01	(.056)	0	(.03)
HOME: Promotion of Maturation and Autonomy			0.02	(.057)	0.05	(.045)	0.03	(.036)
HOME: Play Materials			**0.10 ***	(.058)	**0.24 *****	(.057)	**0.21 *****	(.041)
Neighborhood Environment			0.03	(.048)	-0.05	(.108)	0	(.055)
Income			0	(.041)	0	(.071)	0.01	(.039)
Single Parenthood			**-0.13 ****	(.059)	-0.04	(.04)	**-0.08 ****	(.036)
Average Parental Age			**0.08 ***	(.048)	0.08	(.084)	**0.10 *****	(.037)
Number of Persons in Household			**0.11 ****	(.057)	-0.09	(.048)	-0.02	(.041)
Biological Parents			**0.12 ****	(.058)	**0.11 ***	(.056)	**0.09 ***	(.047)
External Childcare			**-0.07 ***	(.037)	-0.13	(.074)	-0.1	(.054)
IQ	**0.83 *****	(.042)	**0.80 *****	(.044)	**0.48 *****	(.145)	**0.69 *****	(.053)
Adjusted R²	0.5796		0.5946					
MSE	0.6597		0.6362					
Number of components					6		2	
Percent of explained variance in S					0.3276		0.588	
Estimated MSE Prediction Error					0.5442		0.472	

Source: Mannheim Study of Children at Risk. 360 observations. Own calculations. Standard errors are in parentheses: ***significant at 1% level, ** significant at 5 % level, * significant at 10 % level.

As figure 6.3 indicates, a low level of mean standard errors of PCR is achieved by using at least 6 components. The explained variance in S, 32.7 percent, is relatively small and smaller than the adjusted R^2 in column (2).This results from the fact that fewer predictor variables (6 components) are used. On the other hand, imposing a latent factor structure on E leads to uncorrelated predictor variables[36] and overfitting is avoided. The estimated MSE is smaller than in OLS. “Play Materials” and the fact of “living with biological” parents have a significant positive impact on the IQ of the next period according to PCR. The estimated self-productivity is relatively low (0.48). To sum up, it seems PCR can reduce multicollinearity problems, but may have problems in explaining enough variance in S.

Figure 6.3 shows that the estimated MSE for PLSR indicates that two components does about as good a job as possible. On the other hand, PCR requires 6 to 10 components to get similar prediction accuracy. In fact, the second component in PCR even increases the prediction error slightly, suggesting that the combination of predictor variables contained in that component is not strongly correlated with S. Again, that is because PCR constructs components to explain variation in E, but not in S. The PLSR model is much more parsimonious than the PCR model. Column (4) in table 6.2 shows the estimation results of PLSR. While the estimated MSE is lower than in PCR even though only 2 components are used and the explained variance in S is higher and similar to the adjusted R^2 of OLS. In difference to OLS, PLSR avoids multicollinearity problems by choosing orthogonal latent predictors. In difference to PCR, they are chosen such that they can efficiently explain S. According to the PLSR of the simplified technology of skill formation "avoidance of punishment and restriction", "play materials", the "parental age" and "living with biological parents" have a positive effect on the future IQ. Single parenthood seems to have adverse effects. Self-productivity is estimated by 0.69, being lower than in the OLS case, but higher than in the PCR model.

Figure 6.3: Estimated mean sqaured prediction error of PCR and PLSR depending on the number of latent components



[36] PCR as well as PLSR assumes orthogonal latent factors in this study.

6.4 Results

6.4.1 Estimating the role of environmental aspects and HOME-subsores

This section estimates the technology of skill formation specified in equation 6.1 with cognitive, mental and emotional skills by PLSR for different stages of childhood. Measurements were assigned to the emotional, cognitive and mental group as specified in section 6.2.2. Table 6.3 shows the results for the PLSR of the environmental aspects at the age of 3 months on skills measures at the age of 2 years.

Table 6.3: Estimation of Mood, the IQ and the activity level at the age of 2 years based on environmental conditions until the age of 3 month

	(1) **Mood**		(2) **IQ**		(3) **Persistence**	
Interviewer rating of contact person	0	(.029)	0.01	(.029)	-0.03	(.038)
HOME Conversation process with mother and child	**0.05 ***	(.03)	**0.06 ****	(.029)	0.01	(.039)
HOME Mother Child Interaction	-0.01	(.028)	0.02	(.026)	0.01	(.04)
HOME Living Environment	0.01	(.025)	**0.06 ****	(.024)	0.03	(.042)
Low Organic Risk	0.03	(.037)	**0.16 *****	(.036)	0.01	(.044)
Low Psychosocial Risk	**0.05 ***	(.028)	**0.10 *****	(.028)	**0.12 *****	(.037)
Breastfeeding	-0.03	(.029)	0.04	(.023)	**0.07 *****	(.028)
Mother-Child Interaction (Video)	**0.09 *****	(.033)	**0.11 *****	(.031)	0.08	(.047)
Neighborhood Environment	-0.05	(.03)	-0.01	(.026)	0.03	(.036)
Income	-0.01	(.028)	**0.06 *****	(.022)	0.01	(.029)
Single Parenthood	0.04	(.031)	0.04	(.03)	0	(.036)
Parental Age	-0.04	(.03)	0.04	(.03)	0.01	(.036)
Number of Persons in Household	0.02	(.033)	-0.01	(.033)	-0.01	(.042)
Living with biological parents	**0.06 ***	(.035)	0.03	(.025)	0.04	(.049)
Parental Education	-0.05	(.034)	**0.09 *****	(.026)	**0.09 *****	(.034)
Emotional Skills	**0.09 *****	(.032)	**0.07 ****	(.035)	0.01	(.043)
Cognitive Skills	**0.07 ****	(.037)	**0.20 *****	(.044)	**0.09 ****	(.047)
Mental Skills	0.05	(.04)	0.03	(.029)	-0.02	(.045)
Number of components	2		2		2	
RMSECV	1.88		1.29		1.14	

Source: Mannheim Study of Children at Risk. 360 observations. Own calculations. Standard errors are in parentheses: ***significant at 1% level, ** significant at 5 % level, * significant at 10 % level.

At the age of 2 years the malleability of the IQ is high, with cognitive skills of the previous period accounting for about 20 percent (evidence for low self-productivity). Emotional skills of the previous period also have a positive influence on the IQ (0.07). Birth risks are the most important determinants (0.16 and 0.10) followed by the quality of mother-child Interaction (0.11), parental education (0.09), income (0.06) and two HOME subscores, “living environment” (0.06) and the “conversation process with mother and child” (0.06). A decrease in organic risk by one standard deviation relates to 0.16*15=2.4 additional IQ points at the age of 2 years. A decrease in psychosocial risk by a standard deviation is linked to 1.6 additional IQ points. The mother-child interaction is equally important. Remarkably, the parental education has an additional strong positive coefficient on the IQ, even though it is closely related to the aspects covered by psychosocial risk. The mother-child interaction has a significant positive coefficient on mood (0.09), besides the HOME sub-score "Conversation process with mother and child" (0.05) and a low psychosocial risk (0.05). What seems even more important for mood is "living with biological parents" (0.09). This variable may capture several aspects at the very young age. Children not living with their biological parents in infancy have usually been adopted and may have faced difficulties regarding their biological parents. Not all of the issues involved with not living with biological are captured by the HOME or the mother-child interaction. The development of persistence is also driven by a low psychosocial risk (0.12), parental education (0.09) and breastfeeding (0.07), supporting studies that find beneficial effects from breastfeeding (Goodhall et al., 2007).

The results show that the HOME at the age of 3 months captures only a fraction of the relevant determinants. The the mother-child interaction is equally important, a result in line with Blomeyer et al. (2010). The birth risks tend to have even more predictive power on skills at the age of 2 years. Organic risk seems to be mainly related to lower cognitive skills. Psychosocial risk affects all skills, but mental skills (persistence) the most. Material aspects such as income and the living environment are more closely linked to the IQ.

While interpreting the results, it has to be kept in mind that multiple indirect effects of the environment may additionally exist as "skill begets skill" (Cunha et al., 2006). Even cognitive skills at the age of 3 months have already a strong significant coefficient on mood (0.11) at the age of 2 years. So anything that improves the IQ could eventually also improve mood.

Table 6.4 shows results of regressing of the environmental conditions at the age of 2 years on the skills at the age of 4.5 years. A big difference to the results shown in table 6.3 is the strong increase in self-productivity for all skills.[37] For the IQ cognitive skills of the previous period have a coefficient of 0.49, the impact of emotional skills of the previous period on mood amounts to 0.29 and

[37] Note that the coefficients are not exactly equal to the self-productivity as they refer to the latent skills. The latent skills are generally highly correlated with the measurements (>0.8), so a high coefficient gives evidence of a high self-productivity. Alternatively the sole measurements could be used in the regression, but integrating all of them would make the interpretation of the results more diffuse, integrating only few would drop a lot of relevant information on previous period skills.

the impact of previous period mental skills on persistence to 0.28. These results suggest that skills start to become more stable at the age of 4.5 years. Direct-complementarities start to emerge among skills: Cognitive skills have a large coefficient on noncognitive skills. The relationship also goes into the other direction, but to a much smaller extent.

The HOME still captures roughly only half of the determinants that have significant coefficients on the skills even though it includes 87 items at the age of 2 years (compared to 25 at the age of 3 months, see section 6.2.2). By far the most important and sole significant HOME subscore is "play materials" with a coefficient of 0.16 on the IQ, 0.09 on persistence and 0.07 on mood. The coefficient of 0.16 means that an increase in the subscore "play materials" by one standard deviation (which corresponds to a move from the 50^{th} to the 87^{th} percentile) increases the IQ at the age of 4.5 years by 2.4 points. Income and "living with biological parents" are other determinants with a positive, significant coefficient. Especially the latter variable gives evidence that not all aspects of the child-parent relationship are covered by the HOME. The coefficient is even higher for persistence (0.14), which is also influenced by breastfeeding (0.06). Single parenthood negatively affects emotional skills.

All in all, several other variables seem to account for the skill development and outperform the HOME with respect to predictive power on future skills. Table 6.5 shows the results of regression of the environmental conditions at the age of 4.5 years on the skill measurements at the age of 8 years.

The evidence suggests self-productivity to further increase as the coefficient of cognitive skills on the IQ (0.67) rises. It remains relatively low for mental (0.3) and emotional skills (0.27). Cognitive skills foster the noncognitive skills of the subsequent periods to a great extent (the coefficient of cognitive skills on persistence amounts to 0.52, on mood it is 0.11). Like in table 6.4, the HOME subscore "play materials" is the most relevant subscore again (a coefficient of 0.21 on the IQ and 0.16 on persistence). That means an increase of one standard deviation in "play materials" (corresponding to an increase of the 30^{th} to the 91^{th} percentile) is related to an increase of the future IQ by 3.15 points. Additionally, persistence is enhanced, which may in turn positively affect the IQ again and vice versa.

Table 6.4: Estimation of Mood, the IQ and the activity level at the age of 4.5 years from environmental conditions at the age of 2 years

	(1) Mood		(2) IQ		(3) Persistence	
Interviewer rating of contact person	**0.06 ***	(.034)	-0.04	(.028)	-0.03	(.032)
HOME Conversation process with parents	0	(.03)	-0.01	(.026)	-0.04	(.035)
HOME Stimulation of development and language	-0.02	(.034)	0.04	(.026)	0.02	(.029)
HOME Living Environment	0.02	(.035)	0.05	(.034)	0	(.044)
HOME Avoidance and Restriction and Punishment	-0.04	(.03)	-0.04	(.025)	-0.02	(.03)
HOME Emotional Climate	0.03	(.025)	-0.01	(.02)	0.02	(.022)
HOME Promotion of Maturation and Autonomy	0.04	(.031)	0	(.023)	0.02	(.03)
HOME Play Materials	**0.07 ****	(.033)	**0.16 *****	(.035)	**0.09 *****	(.035)
Neighborhood Environment	0	(.034)	0.02	(.028)	-0.05	(.034)
Income	-0.01	(.034)	**0.07 *****	(.02)	0.02	(.039)
Single Parenthood	**-0.07 ****	(.036)	0	(.034)	0	(.038)
Parental Age	-0.04	(.035)	0.05	(.033)	0.03	(.038)
Number of Persons in Household	-0.05	(.04)	0	(.033)	0.02	(.043)
Living with biological parents	0.06	(.037)	**0.06 ***	(.037)	**0.14 *****	(.039)
Breastfeeding	-0.06	(.043)	0.02	(.028)	**0.06 ***	(.033)
Emotional Skills	**0.29 *****	(.051)	**0.10 *****	(.034)	0.02	(.043)
Cognitive Skills	**0.16 *****	(.041)	**0.49 *****	(.043)	**0.33 *****	(.05)
Mental Skills	0.05	(.044)	**0.11 ****	(.051)	**0.28 *****	(.048)
Number of components	2		2		2	
RMSECV	1.75		1.07		0.86	

Source: Mannheim Study of Children at Risk. 360 observations. Own calculations. Standard errors are in parentheses: ***significant at 1% level, ** significant at 5 % level, * significant at 10 % level.

Table 6.5: Estimation of Mood, the IQ and the activity level at the age of 8 years from environmental conditions at the age of 4.5 years

	(1) Mood		(2) IQ		(3) Persistence	
Interviewer rating of contact person	0.01	(.026)	-0.04	(.034)	-0.07	(.041)
HOME Conversation process with parents	**0.04 ***	(.023)	0.04	(.036)	0.01	(.045)
HOME Stimulation of development and language	-0.02	(.025)	-0.05	(.033)	-0.07	(.039)
HOME Living Environment	0.02	(.026)	0.03	(.041)	-0.06	(.042)
HOME Avoidance and Restriction and Punishment	0.03	(.02)	0.04	(.03)	-0.01	(.042)
HOME Emotional Climate	0.01	(.021)	-0.01	(.03)	0	(.032)
HOME Promotion of Maturation and Autonomy	0.04	(.027)	0.04	(.034)	**0.11 *****	(.047)
HOME Play Materials	0.02	(.023)	**0.21 *****	(.041)	**0.16 *****	(.037)
Neighborhood Environment	-0.01	(.029)	-0.02	(.049)	-0.01	(.05)
Income	0.03	(.024)	0	(.039)	0.02	(.037)
Single Parenthood	-0.04	(.026)	**-0.07 ****	(.036)	-0.01	(.045)
Average Parental Age	**-0.06 ****	(.027)	**0.07 ***	(.039)	0.03	(.04)
Number of Persons in Household	0	(.025)	-0.03	(.039)	0	(.045)
Living with biological Parents	0	(.024)	**0.09 ****	(.046)	0.04	(.044)
External Childcare	0.03	(.027)	-0.1	(.052)	-0.03	(.049)
Emotional Skills	**0.27 *****	(.04)	**0.08 ***	(.047)	0.01	(.051)
Cognitive Skills	**0.11 *****	(.031)	**0.67 *****	(.06)	**0.52 *****	(.064)
Mental Skills	0.04	(.033)	0.06	(.058)	**0.30 *****	(.067)
Number of components	2		2		2	
RMSECV	1.7		1.05		1.02	

Source: Mannheim Study of Children at Risk. 360 observations. Own calculations. Standard errors are in parentheses: ***significant at 1% level, ** significant at 5 % level, * significant at 10 % level.

Interestingly, all other HOME subscores do not seem very relevant for the IQ. “Living with biological parents” again provides additional predictive power (0.09) as well as single parenthood (-0.07) and parental age (0.07). Astonishingly, the coefficient of “parental age” on emotional skills points just to the opposite direction (-0.06) and is significant. This suggests that children of older parents may turn out smarter, but children of younger parents may turn out happier. It is an example that investments not necessarily go into one direction only and reveals a possible disadvantage of large aggregates. Mood at the age of 8 years is related to the “conversation process with the parents” (0.04). Another relevant HOME subscore is the “promotion of maturation and autonomy”. While having a positive coefficient on all skills it is significant only for persistence (0.11). Finally, table 6.6 shows the results of regression of the environmental conditions at the age of 8 years on the skills at the age of 11 years.

Again, self-productivity of noncognitive skills only slightly increases (0.37 for emotional and 0.33 for mental skills). In contrast, cognitive skills are relatively stable at the age of 11 years (0.84). Direct complementarities exist particularly among cognitive and mental skills. Those results are in line with previous studies (Blomeyer et al., 2009; Coneus et al., 2011). A difference is that several HOME aspects at the age of 8 years are still linked to the skills at the age of 11 years, suggesting some degree of plasticity. While the fundament of cognitive skill is set in early childhood continuous practise may help in maintaining a higher IQ. The age of 8 years is the only period, in which the HOME alone accounts for all of the relevant determinants. The most important subscores are “materials and experiences promoting development” (0.16 on cognitive skills, 0.06 on mental skills) and “active stimulation” (0.04 on mood, 0.08 on the IQ and 0.08 on persistence). Upon that “emotional climate” plays a role for mental skills (0.07) and “activities promoting development” for emotional skills (0.05).

All in all, the results suggest that cognitive skills stabilize faster than noncognitive skills. This is in line with studies that suggest noncognitive skills to be more malleable (Cunha and Heckman, 2007). On the other hand, if the HOME is not aggregated, certain subscores still play a role at the age of 8 years. This does not contradict the fact that early childhood is very important as the results related to the birth risks and mother-child interaction show. But the results suggest that investments in infancy should be complemented by investments in later childhood to yield success.

To test the robustness of the results and to look at the long-term consequences of investments during infancy, the skills of the previous periods are substituted by earlier environmental conditions and regressed on the skills at the age of 11 years. For this, S_4 are substituted by E_3 and S_3 in equation 1 for t=5. The S_3 are then substituted by E_2 and S_2. S_2 are finally substited by S_1 and E_1 and S_1 by the initial birth risk, E_0. Equations 6.2 to 6.8 are applied. Table 6.7. shows the results.

Table 6.6: Estimation of Mood, the IQ and the activity level at the age of 11 years from environmental conditions at the age of 8 years

	(1) Mood		(2) IQ		(3) Persistence	
HOME Paternal Engagement	-0.03	(.028)	0	(.045)	-0.06	(.035)
HOME Emotional and verbal responsitivty	0.03	(.027)	0	(.038)	0.02	(.031)
HOME Active Stimulation	**0.04 ***	(.023)	**0.08 ****	(.04)	**0.08 *****	(.03)
HOME Material Environment	0.03	(.026)	0	(.038)	-0.04	(.031)
HOME Activities promoting development	**0.05 ****	(.023)	-0.01	(.04)	0	(.032)
HOME Emotional Climate	0.02	(.028)	-0.07	(.039)	**0.07 ****	(.031)
HOME Promotion of Social Maturity	**0.05 ***	(.026)	0.01	(.044)	0.01	(.036)
HOME Materials and Experiences promoting development	0.02	(.023)	**0.16 *****	(.037)	**0.06 ****	(.03)
Neighborhood Environment	0.03	(.034)	0.02	(.051)	0.06	(.048)
Income	0.04	(.031)	0.02	(.034)	0.02	(.03)
Single Parenthood	0	(.029)	-0.02	(.049)	-0.07	(.036)
Average Parental Age	-0.03	(.03)	0.01	(.051)	0.02	(.037)
Number of Persons in Household	0	(.034)	-0.06	(.052)	-0.02	(.052)
Living with biological Parents	0.03	(.031)	0.06	(.048)	**0.10 *****	(.04)
Emotional Skills	**0.37 *****	(.051)	**0.18 *****	(.045)	**0.09 ****	(.045)
Cognitive Skills	0.03	(.054)	**0.84 *****	(.056)	**0.40 *****	(.048)
Mental Skills	-0.06	(.05)	**0.18 *****	(.057)	**0.33 *****	(.037)
Number of components	3		3		3	
RMSECV	1.65		1.13		0.8	

Source: Mannheim Study of Children at Risk. 360 observations. Own calculations. Standard errors are in parentheses: ***significant at 1% level, ** significant at 5 % level, * significant at 10 % level.

There exist several differences to the results previously presented in this section. Psychosocial risk has no significant coefficient anymore, but organic risk is even more harmful. It seems that organic risk has stronger adverse long-term effects relative to psychosocial risk, which is more detrimental for skills at the age of 2 years. Psychosocial risk is rather related to other adverse conditions later in childhood and its coefficient is absorbed by those aspects. Parental education is a better predictor for persistence and the IQ. The mother-child interaction has a long-term predictive power on mood and the IQ at the age of 11 years. Breastfeeding has a significant positive coefficient on the IQ and persistence in late childhood. The subscore “play materials” has significant coefficients at the age of 2 years and 4.5 years on both, the IQ and persistence. This confirms the results presented earlier in this section. At the age of 4.5 years single parenthood is inversely related with skills. Even at the age of 8 years several subscores have predictive power, in particular “materials and experiences promoting development” and “active stimulation”.

Table 6.7: Estimation of skills at the age of 11 years from all environmental conditions

		(1) Mood		(2) IQ		(3) Persistence	
3 months	Interviewer rating of contact person	-0.01	(.023)	-0.06	(.035)	0	(.032)
	HOME Conversation process with mother and child	**0.04 ***	(.023)	0.02	(.043)	-0.05	(.04)
	HOME Mother Child Interaction	-0.02	(.023)	0	(.035)	0	(.036)
	HOME Living Environment	0.01	(.021)	0	(.034)	0	(.039)
	Low Organic Risk	0.03	(.03)	**0.26 *****	(.056)	**0.14 *****	(.041)
	Low Psychosocial Risk	-0.02	(.022)	0.03	(.033)	0.05	(.034)
	Mother-Child Interaction (Video)	**0.06 ****	(.025)	**0.13 *****	(.047)	0.05	(.046)
	Neighborhood Environment	0.01	(.018)	0	(.033)	-0.06	(.033)
	Income	-0.01	(.014)	0	(.028)	0.03	(.03)
	Single Parenthood	0.02	(.019)	-0.04	(.035)	0.01	(.033)
	Parental Age	-0.03	(.016)	0.01	(.019)	0	(.016)
	Number of Persons in Household	-0.03	(.026)	-0.03	(.042)	0.03	(.043)
	Living with biological parents	**0.03 ***	(.02)	-0.06	(.034)	-0.01	(.029)
	Parental Education	-0.01	(.02)	**0.10 *****	(.036)	**0.08 *****	(.033)
2 years	Interviewer rating of contact person	0	(.018)	-0.02	(.029)	-0.04	(.024)
	HOME Conversation process with parents	**0.05 ****	(.021)	-0.03	(.032)	-0.04	(.035)
	HOME Stimulation of development and language	0	(.016)	0	(.026)	-0.03	(.025)
	HOME Living Environment	0.02	(.021)	0.03	(.044)	0.05	(.041)
	HOME Avoidance and Restriction and Punishment	0	(.017)	-0.05	(.027)	-0.02	(.03)
	HOME Emotional Climate	0.01	(.017)	-0.05	(.027)	0.02	(.029)
	HOME Promotion of Maturation and Autonomy	0	(.018)	-0.04	(.032)	-0.04	(.035)
	HOME Play Materials	0.02	(.022)	**0.14 ****	(.065)	**0.09 ****	(.045)
	Neighborhood Environment	-0.01	(.021)	-0.01	(.029)	0	(.034)
	Income	-0.01	(.014)	0.03	(.023)	0.02	(.025)
	Single Parenthood	**-0.06 *****	(.022)	-0.04	(.038)	-0.02	(.038)
	Parental Age	-0.03	(.016)	0.01	(.019)	0	(.016)
	Number of Persons in Household	-0.05 **	(.022)	-0.01	(.041)	-0.07	(.036)
	Living with biological parents	0.03	(.019)	-0.01	(.038)	0.04	(.028)
	Breastfeeding	-0.04	(.024)	**0.06 ****	(.028)	**0.06 ****	(.029)
4.5 years	Interviewer rating of contact person	0	(.02)	0.02	(.034)	-0.04	(.028)
	HOME Conversation process with parents	**0.08 *****	(.023)	0.01	(.038)	0.03	(.038)
	HOME Stimulation of development and language	-0.01	(.015)	0	(.026)	-0.03	(.024)
	HOME Living Environment	0.02	(.021)	0.03	(.037)	-0.05	(.038)
	HOME Avoidance and Restriction and Punishment	0.03	(.021)	0.01	(.03)	0.01	(.032)
	HOME Emotional Climate	**0.03 ***	(.019)	-0.02	(.031)	0.02	(.033)
	HOME Promotion of Maturation and Autonomy	**0.05 *****	(.02)	0.04	(.033)	0.05	(.035)
	HOME Play Materials	0.01	(.02)	**0.18 *****	(.054)	**0.18 *****	(.047)
	Neighborhood Environment	-0.02	(.023)	-0.01	(.046)	0.01	(.047)
	Income	0	(.019)	-0.02	(.032)	-0.05	(.029)
	Single Parenthood	-0.02	(.019)	**-0.09 *****	(.039)	**-0.07 ****	(.035)
	Average Parental Age	-0.03	(.016)	0.01	(.019)	0	(.016)
	Number of Persons in Household	-0.04	(.019)	-0.06	(.032)	-0.02	(.027)
	Living with biological Parents	0.02	(.02)	0.01	(.037)	0.04	(.029)
	External Childcare	**0.06 *****	(.025)	-0.06	(.053)	-0.06	(.043)
8 years	HOME Paternal Engagement	-0.03	(.021)	0.05	(.05)	-0.01	(.036)
	HOME Emotional and verbal responsitivty	0.01	(.022)	0.03	(.028)	**0.07 *****	(.031)
	HOME Active Stimulation	0.02	(.022)	**0.13 *****	(.041)	**0.10 *****	(.033)
	HOME Material Environment	0.01	(.017)	-0.05	(.035)	-0.02	(.034)
	HOME Activities promoting development	0.02	(.017)	0.03	(.034)	0.01	(.037)
	HOME Emotional Climate	0	(.023)	-0.03	(.039)	**0.12 *****	(.039)
	HOME Promotion of Social Maturity	0.03	(.019)	0.02	(.041)	0.05	(.037)
	HOME Materials and Experiences promoting development	0	(.019)	**0.18 *****	(.046)	**0.10 *****	(.035)
	Neighborhood Environment	0.01	(.024)	0.04	(.045)	0.07	(.05)
	Income	0.02	(.021)	0.02	(.028)	0.01	(.028)
	Single Parenthood	0	(.023)	0.04	(.057)	-0.01	(.04)
	Average Parental Age	-0.03	(.016)	0.01	(.019)	0	(.016)
	Number of Persons in Household	0	(.023)	-0.04	(.042)	0.02	(.042)
	Living with biological Parents	0.01	(.02)	**0.10 ****	(.049)	**0.09 *****	(.034)
Number of components		3		3		3	
RMSECV		2.08		1.83		1.13	

Source: Mannheim Study of Children at Risk. 360 observations. Own calculations. Standard errors are in parentheses: ***significant at 1% level, ** significant at 5 % level, * significant at 10 % level.

A striking result is the close similarity to the predictive power of the variables on the IQ and persistence until the age of 4.5 years. The results remind the coefficients in tables 6.3 to 6.6 that predict the IQ. The reason for this could result from the high coefficients of IQ on persistence (direct complementarity). As shown in the earlier regressions, the IQ has a great predictive power on persistence. Direct complementarities could also explain why environmental aspects at the age of 4.5 years are relevant for mood at the age of 11 years, even though they have not been relevant for mood at the age of 8 years (see table 6.5).

To sum up, this section suggests that other factors besides the HOME play a role in predicting skills of future periods - especially until the age of 4.5 years. The analysis confirms results of previous studies that investigate the predictive power of HOME subscores on later academic performance and find play materials to be the most relevant subscore (Bradley and Caldwell, 1984; Wolfgang and Stakenas, 1985).

The predictive power of the HOME score could be stronger if it is not aggregated to subscores. Section 6.4.2 splits off the HOME into its single items and preserves all the contained information. This also sheds some more light on the meaning of the different HOME subscores that have been discussed in this section.

6.4.2 Estimating the role of environmental aspects and HOME items

Instead of using the aggregated HOME subscores as predictor variables of the skills, this section integrates all single items in the model. As a result the matrix E contains up to 125 environmental variables (at age of 4.5 years). As described in section 6.3, the PLSR tends to profit from additional variables even if they are highly collinear. On the other hand, presenting the coefficient of each single item would boost the size of the tables. Thus, I always present the five highest absolute coefficients of the environmental aspects on the respective skills. Skills of the previous periods are integrated in the model in an identical way as in section 6.4.1, but are not discussed here. Table 6.8 shows the results of the regression of the environmental aspects at the age of 3 months on skill measures at the age of 2 years. Even though the available data increases, the RMSECV can be reduced from 1.29 to 1.16 for the prediction of the IQ and from 1.14 to 1.13 for the prediction of persistence. For mood it is slightly higher. The results presented in table 6.3 are confirmed.

The IQ at the age of 2 years is mainly linked to the birth risks, with both risks being approximately equally important, followed by the mother-child interaction and income. The integration of all the HOME items slightly reduces the contribution of organic risk (from 0.16 to 0.10), but not of psychosocial risk (0.10 to 0.11) and breastfeeding (0.06). No HOME items are found among the strongest predictors of the IQ, but several have positive coefficients on noncognitive skills. Adequate living conditions and praising the child are linked to patterns that drive persistence. Maternal behaviour during the conversation process, unforcefulness, eloquence during the interview and maternal interest have positive predictive power on mood. Organic risk and income are more closely related to the IQ. The mother-child interaction and psychosocial risk have a strong predictive power on all skills. Table 6.9 shows the results for the regression of the environmental aspects at the age of 2 years on skill measures at the age of 4.5 years.

Table 6.8: Estimation of Mood, the IQ and the activity level at the age of 2 years by environmental conditions until the age of 3 month, five largest environmental coefficients

Mood	Mother Child Interaction (Video)		**0.08*** **	0.03
	Living with biological parents		0.05	0.032
	Low Psychosocial Risk		**0.05***	0.026
	Mother talks unforcedly, is eloquent	Conversation process	**0.05****	0.021
	Mother is active during the interview (asks questions, etc.)	Conversation process	**0.04****	0.022
	Number of components		2	
	RMSECV		2.03	
IQ	Low Psychoscoial Risk		**0.11*****	0.035
	Low Organic Risk		**0.10*****	0.039
	Mother-Child Interaction (Video)		**0.10*****	0.032
	Income		**0.09*****	0.026
	Breastfeeding		**0.06***	0.037
	Number of components		3	
	RMSECV		1.16	
Persistence	Low Psychosocial Risk		**0.12*****	0.031
	Parental Education		**0.10*****	0.03
	Adequate living conditions (not too dark, loud, narrow)	Living Environment	**0.09***	0.045
	Mother Child Interaction (Video)		**0.08***	0.042
	During visit mother praises child at least once	Conversation process	**0.08***	0.044
	Number of components		2	
	RMSECV		1.13	

Source: Mannheim Study of Children at Risk. 360 observations. Own calculations. Standard errors are in parentheses: ***significant at 1% level, ** significant at 5 % level, * significant at 10 % level. HOME items in *italics*

Again, the integration of all the distinct HOME items can reduce the RMSECV from 1.05 to 0.83 for cognitive skills even though more information is included in the model. For noncognitive skills it slightly increases.

In difference to table 6.8 the results in table 6.9 are dominated by HOME items. One reason may result from the fact that the HOME at the age of 2 years contains 87 items (instead of 25 at the age of 3 months). Another reason is the additional information gained by disaggregating the HOME (compare with table 6.4). The items of the subscore "play materials" are the most common among the relevant predictors – especially for the IQ. Owning a table and a chair suited for children (e.g. a place to sit and practise) as well as equipment to paint is linked to patterns that improve cognitive skills. Toys to drive are likely to be beneficial for the cognitive abilities, too. The other two relevant items rather stem from the patterns of conversation between the parents and the child, answering the child's questions and helping it to improve. This shows an important issue: The single items should not be understood as the sole relevant aspects educators and parents should adress. A variety of play materials in combination with parents that take care of the child's verbal abitlites indicates that it is important for the IQ to have parents that actively help the child in training various tasks. A lot of toys highlight that parents take care to improve their child's abilities.

Table 6.9: Estimation of Mood, the IQ and the activity level at the age of 4.5 years by environmental conditions until the age of 2 years, five largest environmental coefficients

Mood	*Child has toys that requiring hand movement (e.g. coloring books)*	Play Material	**0.10*****	0.033
	Child has toy that requires free movement	Play Material	**0.07****	0.034
	Parents praise child at least twice during interview	Emotional Climate	**0.07*****	0.03
	No disturbances by traffic, commerce in neighborhood	Neighborhood environment	**0.07****	0.028
	Parents motivate child to do something idependently	Promotion of Maturation and Autonomy	**0.06***	0.034
	Number of components		3	
	RMSECV		1.98	
IQ	*Child has a child table and chair or equivalent*	Play Material	**0.09*****	0.029
	Family has painting equipent or material requiring hand movement	Play Material	**0.07*****	0.024
	Parents verbally react to questions and wishes of the child	Emotional Climate	**0.06*****	0.027
	Child has a toy to drive	Play Material	**0.06****	0.027
	Parents expand verbalizations of the child (to full sentences)	Stimulation of development and language	**0.05*****	0.021
	Number of components		3	
	RMSECV		0.83	
Persistence	Living with biological parents		**0.10*****	0.027
	Parents set reasonable limits for child	Promotion of Maturation and Autonomy	**0.08*****	0.03
	Child has toy that requires free movement	Play Material	**0.07*****	0.029
	No excessive interference in childs' actions during interview	Stimulation of development and language	**0.07****	0.031
	If child calls for help, parents motivate child to help itself	Emotional Climate	**0.06*****	0.025
	Number of components		3	
	RMSECV		1.14	

Source: Mannheim Study of Children at Risk. 360 observations. Own calculations. Standard errors are in parentheses: ***significant at 1% level, ** significant at 5 % level, * significant at 10 % level. HOME items in *italics*

However, play materials also predict mood. Aspects such as praising and motivating the child seem relevant, too. Disturbances in the neighbourhood such as traffic are inversely related. With respect to persistence, play materials have one significant item (toys that require free hand movement). The parent-child interaction tends to be more important. Parents, who set reasonable limits, motivate the child and do not excessively interrupt the child's actions, are related to a higher persistence. This indicates that parents who have a very harmonious and stimulating relationship with their children can enhance its noncognitive skills.

The coefficient of "living with biological parents" is smaller than in table 6.4 (0.1 instead of 0.14), but still might capture additional important patterns. Table 6.10 shows the results for the regression of the environmental aspects at the age of 4.5 years on skill measures at the age of 8 years.

Table 6.10: Estimation of Mood, the IQ and the activity level at the age of 8 years by environmental conditions until the age of 4.5 years, five largest environmental coefficients

Mood	*Child can express negative emotions without having to expect sanctions*	Avoidance and Restriction and Punishme	**0.06*****	0.027
	Family has a pet	Living Environment	**0.06****	0.027
	Acceptance of child	Contact Person	**0.05****	0.025
	Parents set reasonable limits for child	Promotion of Maturation and Autonomy	**0.05***	0.026
	Parents do not continously patronize child	Promotion of Maturation and Autonomy	**0.05****	0.024
	Number of components		3	
	RMSECV		1.89	
IQ	*Parents teach the child numbers and letters*	Stimulation of development and language	**0.07*****	0.019
	Child has toys that prepare learning numbers	Play Material	**0.07*****	0.018
	Parents teach the child colors and shapes	Stimulation of development and language	**0.05****	0.024
	Child has toy to drive	Play Material	**0.05***	0.028
	Child has at least three puzzles	Play Material	**0.05***	0.024
	Number of components		3	
	RMSECV		0.97	
Persistence	*Child has toys that prepare learning numbers*	Play Material	**0.07*****	0.018
	Parents teach the child colors and shapes	Stimulation of development and language	**0.06*****	0.019
	Child has toys that prepare learning letters	Play Material	**0.05*****	0.018
	Acceptance of child	Contact Person	**0.04*****	0.018
	Parents teach child to be polite	Promotion of Maturation and Autonomy	**0.04***	0.022
	Number of components		3	
	RMSECV		1.01	

Source: Mannheim Study of Children at Risk. 360 observations. Own calculations. Standard errors are in parentheses: ***significant at 1% level, ** significant at 5 % level, * significant at 10 % level. HOME items in *italics*

Among the environmental aspects at the age of 4.5 years the home items dominate in terms of predictive power. Other variables besides the HOME are less relevant compared to the results shown in table 6.5. This indicates that an integration of 101 separate HOME items provides additional information. Also the RMSECV of the IQ and persistence slightly decrease (from 1.05 to 0.97 and from 1.02 to 1.01, respectively).

Among the predictors of the IQ at the age of 8 years items of the "play materials" subscore still dominate. In difference to the age of 2 years (table 6.8), when toys that improve coordination and verbal interaction with the child were beneficial, the child should get into contact with puzzles, numbers, letters and shapes at the age of 4.5 years. Again, the toys alone are likely not to help much. They should be complemented by adequate parental support.

Persistence has similar predictors (toys preparing to learn numbers and toys to drive). In addition the “general acceptance of the child” that was observed during the interview (not being part of the HOME score) and learning to be polite are linked to persistence. While the predictors of mood were still closely related to some of the IQ predictors at earlier ages they tend to be more distinct at the age of 4.5 years. Being able to express emotions without having to expect sanctions, owning a pet, parents setting reasonable limits and avoidance of continuous patronization are strong indicators of relevant patterns. Just like for persistence the general acceptance of the child during the interview is important.

To sum up, at the age of 4.5 years HOME items dominate among the relevant variables. While teaching the child numbers, shapes and letters (with toys) enhances the IQ. A harmonious and stimulating parent-child interaction is beneficial for mood. Persistence lies in between.

Table 6.11 shows that even at the age of 8 years several items have predictive power on future skills (at the age of 11 years). The relevant predictors of cognitive skills move away from play materials to parental support of reading, participating at courses or library visits. This confirms the presumptions made for earlier periods: Not the presence of toys and activies alone enhances skills, but the combination of possibilities to practise various tasks with adaequate parental support. The external environment now gains importance relative to the family environment. For both, the cognitive and the mental skills, teaching the child to perform certain tasks in the household (and tidying up) can be beneficial.

In late childhood the most important variables for mood shift towards other dimensions such as trips or reasonable TV use. Just like in the previous periods, emotional skills depend less on training, but more on a harmonious parent-child interaction. Motivating the child, not being depressed, setting reasonable limits and trips are related to factors enhancing the mood.

With respect to policy implications, the results should not be understood in a way that only the HOME items with the largest significant coefficients need to be addressed by interventions. They can be understood as strong signals of underlying latent factors that are crucial. Thus, a variety of play materials is a signal that the parents are keen on provding possibilities to their child that train motor or reading abilities. Providing toys to children is important, but alone it will not help to improve their cognition. It needs to be complemented by parents assisting the child play and taking care of training their child's abilties. If children are rather low on noncognitive skills, interventions should improve the parent-child relationship in other directions. A harmonious and stimulating parent-child relationship that promotes motivation, independence and autonomy (in the household) seems particularly important.

Table 6.11: Estimation of Mood, the IQ and the activity level at the age of 11 years by environmental conditions until the age of 8 years, five largest environmental coefficients

Mood	*Parents have not been depressed in presence of child during last week*	Emotional Climate	**0.06****	0.026
	Parents motivate child to participate in interview	Emotional and verbal responsitivty	**0.05***	0.029
	Family uses TV in a reasonable way	Active Stimulation	**0.04*****	0.019
	Parents set reasonable limits for child	Promotion of Social Maturity	**0.04*****	0.017
	Parents took child on a trip of at least 50 km recently	Activities promoting development	**0.04***	0.022
	Number of components		3	
	RMSECV		1.59	
IQ	*Child is encouraged to read*	Emotional and verbal responsitivty	**0.11*****	0.034
	Family owns a dictionary and motivates child to use it	Materials, Experiences promoting developmer	**0.09*****	0.024
	Parents expect child to indepedantly do routines in household	Promotion of Social Maturity	**0.06****	0.025
	Parents promote talents of the child (in courses,institutions)	Active Stimulation	**0.05****	0.026
	Child owns a library card and parents support libary visits	Active Stimulation	**0.05*****	0.022
	Number of components		3	
	RMSECV		0.77	
Persistence	*Parents promote talents of the child (in courses,institutions)*	Active Stimulation	**0.08*****	0.019
	Family motivates and enables child to pursue a hobby	Active Stimulation	**0.07*****	0.021
	Parents didn't lose control while dealing with child during last week	Emotional Climate	**0.07*****	0.021
	Parents have not been depressed in front of child during last week	Emotional Climate	**0.05*****	0.023
	Parents expect child to tidy up	Promotion of Social Maturity	**0.05*****	0.021
	Number of components		3	
	RMSECV		0.95	

Source: Mannheim Study of Children at Risk. 360 observations. Own calculations. Standard errors are in parentheses: ***significant at 1% level, ** significant at 5 % level, * significant at 10 % level. HOME items in *italics*

6.4.3 Estimating the role of environmental aspects for social outcomes

Skills that are produced by investments determine social outcomes. Depending on the task, combinations of different skills may be necessary. It is known that cognitive skills enhance economic outcomes during the life cycle (Hanushek and Wößman, 2008). Coneus et al. (2011) show that cognitive skills are the most important of the three skills for school outcomes, mental skills are in second place and emotional skills in third place. Combined the two latter are approximately as important as cognitive skills. Thus, these aspects are not examined again. In contrast, as the study focuses on the optimal composition of various investments for the child functional levels. The PLSR offers the opportunity to estimate response variables choosing from a variety of correlated predictors, so all environmental aspects of the respective previous periods are integrated. To use the child functional levels as responses rather than skills is also a useful way to check the robustness of the results.

Table 6.12 shows the results of regressing environmental aspects of the ages between 3 months and 8 years on the child functional levels in the family, among peers, regarding interests, in school and the child's autonomy (see section 6.2.3). Like in section 6.4.2., birth risks play an important role for predicting the outcomes at the age of 11 years. In particular, organic risk tends to have adverse long-term effects, which is in line with the results presented in table 6.7. The early HOME is not relevant, but the mother-child interaction has a significant predictive power on the child's autonomy. Parental education and breastfeeding are better predictors for school outcomes and interests. This indicates that not a stimulating environment alone promotes academic success, but also parents who may give more attention to education. Interestingly, a low parental age during all periods increases the level of autonomy while the number of persons in the household has a positive relationship in several periods.

Play materials at the ages of 2 and 4.5 years are strong predictors for all functional levels in the same way they are for skills. This confirms the relevance of parents promoting stimulation through play materials. This is in line with previous studies that examined the predictive power of HOME subscores on later academic performance (Bradley and Caldwell, 1984; Wolfgang and Stakenas, 1985). "Avoidance of punishment and restriction" does not seem to be beneficial regarding the functional level in the family, in interests and at school: The regression coefficients are significantly negative.

A certain degree of rules and restriction could enhance social progress. Single parenthood mainly has negative consequences for the functional level among peers. This again indicates possible problems that may arise due to aggregation of all HOME items. The HOME subscores at the age of 8 years all relate to high functional levels except for autonomy. Emotional climate is particularly relevant for family and peer relationships, active stimulation is the most important for interests, school outcomes and peer relations, promotion of social maturity helps for all of the five functional levels.

The high significance of HOME subscores at the age of 8 years confirms the prior results of this study: Advantageous conditions during early childhood should be followed by further investments during middle to late childhood to eventually yield positive outcomes.

Table 6.12: Estimation of the child functional levels at the age of 11 years by environmental conditions until the age of 8 years

		(1) Family		(2) Peers		(3) Leisure		(4) School		(5) Autonomy	
3 months	Interviewer rating of contact person	-0.02	(.022)	-0.03	(.023)	-0.01	(.024)	-0.03	(.021)	-0.01	(.026)
	HOME Conversation process with mother and child	-0.03	(.028)	-0.02	(.025)	-0.03	(.02)	0	(.028)	0.01	(.029)
	HOME Mother Child Interaction	-0.04	(.025)	0	(.021)	0.02	(.026)	-0.03	(.022)	-0.03	(.028)
	HOME Living Environment	0	(.024)	0.03	(.023)	0.03	(.032)	-0.01	(.022)	0	(.023)
	Low Organic Risk	**0.05** *	(.032)	**0.08** ***	(.031)	**0.11** ***	(.032)	**0.15** ***	(.032)	**0.10** ***	(.038)
	Low Psychosocial Risk	**0.06** ***	(.024)	0.03	(.022)	**0.04** **	(.026)	0.03	(.019)	0.01	(.026)
	Mother-Child Interaction (Video)	0.01	(.026)	0.03	(.024)	0.02	(.026)	0.03	(.025)	**0.07** ***	(.03)
	Neighborhood Environment	-0.03	(.024)	-0.02	(.022)	-0.02	(.022)	0	(.019)	-0.03	(.026)
	Income	-0.02	(.022)	-0.01	(.017)	0.03	(.016)	**0.04** ***	(.015)	**0.03** *	(.017)
	Single Parenthood	0.01	(.027)	-0.01	(.021)	0	(.015)	0	(.021)	0	(.025)
	Parental Age	-0.02	(.019)	-0.03	(.017)	0	(.016)	0.01	(.017)	**-0.06** ***	(.018)
	Number of Persons in Household	0.05	(.03)	0.05	(.028)	0	(.023)	0.01	(.025)	**0.05** **	(.027)
	Living with biological parents	0.02	(.024)	0.01	(.017)	0.02	(.015)	-0.01	(.018)	0	(.023)
	Parental Education	0.03	(.02)	0.02	(.02)	**0.08** ***	(.025)	**0.10** ***	(.022)	0.02	(.024)
2 years	Interviewer rating of contact person	-0.02	(.02)	-0.01	(.021)	-0.02	(.021)	0	(.019)	0	(.026)
	HOME Conversation process with parents	0.01	(.022)	-0.01	(.019)	0.01	(.021)	-0.02	(.021)	-0.01	(.023)
	HOME Stimulation of development and language	-0.03	(.02)	0	(.018)	-0.01	(.021)	-0.02	(.019)	0.01	(.023)
	HOME Living Environment	0.02	(.025)	0.02	(.024)	0.02	(.026)	0.02	(.027)	-0.02	(.03)
	HOME Avoidance and Restriction and Punishment	**-0.05** **	(.022)	0	(.016)	**-0.04** **	(.018)	**-0.04** ***	(.016)	-0.01	(.025)
	HOME Emotional Climate	0	(.019)	-0.01	(.016)	-0.02	(.017)	0	(.017)	-0.01	(.021)
	HOME Promotion of Maturation and Autonomy	-0.01	(.02)	0.01	(.018)	-0.01	(.023)	-0.02	(.018)	0.02	(.022)
	HOME Play Materials	**0.06** ***	(.026)	**0.10** ***	(.03)	**0.07** ***	(.024)	**0.08** ***	(.029)	**0.06** *	(.037)
	Neighborhood Environment	0	(.026)	-0.01	(.021)	0	(.021)	0	(.02)	-0.03	(.027)
	Income	0	(.02)	-0.03	(.018)	0.01	(.018)	0.02	(.013)	0.01	(.017)
	Single Parenthood	-0.04	(.029)	**-0.06** ***	(.024)	-0.05	(.017)	0	(.026)	0	(.028)
	Parental Age	-0.02	(.019)	-0.03	(.017)	0	(.016)	0.01	(.017)	**-0.06** ***	(.018)
	Number of Persons in Household	**-0.07** ***	(.027)	-0.05	(.024)	-0.01	(.023)	-0.01	(.026)	0.04	(.03)
	Living with biological parents	**0.04** *	(.022)	0.01	(.018)	0.02	(.013)	0.02	(.021)	**0.04** *	(.022)
	Breastfeeding	0	(.023)	0.01	(.019)	**0.06** **	(.026)	**0.05** ***	(.018)	**0.04** *	(.026)
4.5 years	Interviewer rating of contact person	-0.02	(.023)	0.01	(.023)	-0.01	(.022)	0	(.019)	0.02	(.027)
	HOME Conversation process with parents	0.04	(.029)	0.03	(.026)	0.04	(.028)	0.04	(.024)	0.04	(.027)
	HOME Stimulation of development and language	**-0.04** **	(.02)	0	(.018)	-0.01	(.02)	-0.02	(.018)	0.01	(.023)
	HOME Living Environment	0.04	(.024)	**0.04** *	(.021)	0.01	(.026)	0.02	(.02)	-0.01	(.028)
	HOME Avoidance and Restriction and Punishment	0.02	(.021)	0.01	(.022)	0	(.018)	0.01	(.018)	-0.02	(.025)
	HOME Emotional Climate	0.01	(.021)	0	(.02)	-0.03	(.023)	-0.01	(.018)	0.01	(.02)
	HOME Promotion of Maturation and Autonomy	**0.07** ***	(.022)	**0.05** ***	(.016)	0.02	(.025)	0.03	(.02)	0.02	(.025)
	HOME Play Materials	**0.06** ***	(.018)	**0.08** ***	(.02)	**0.06** ***	(.021)	**0.07** ***	(.021)	**0.06** *	(.031)
	Neighborhood Environment	-0.01	(.029)	0	(.028)	0.01	(.021)	0.02	(.027)	0.01	(.031)
	Income	-0.01	(.019)	-0.03	(.02)	0	(.019)	-0.02	(.019)	0.01	(.024)
	Single Parenthood	-0.02	(.028)	**-0.05** **	(.022)	-0.03	(.019)	-0.03	(.022)	0	(.026)
	Average Parental Age	-0.02	(.019)	-0.03	(.017)	0	(.016)	0.01	(.017)	**-0.06** ***	(.018)
	Number of Persons in Household	-0.04	(.023)	-0.03	(.02)	-0.02	(.02)	-0.01	(.021)	0.04	(.024)
	Living with biological parents	**0.04** **	(.021)	0.03	(.02)	**0.04** *	(.013)	0.02	(.02)	0.03	(.022)
	External Childcare	-0.03	(.037)	0.02	(.032)	-0.04	(.029)	-0.04	(.031)	-0.02	(.036)
8 years	HOME Paternal Engagement	0.02	(.028)	0.04	(.027)	**0.06** ***	(.026)	0.02	(.027)	-0.02	(.03)
	HOME Emotional and verbal responsitivty	**0.08** ***	(.022)	**0.07** ***	(.019)	**0.08** ***	(.023)	**0.04** *	(.019)	0.02	(.02)
	HOME Active Stimulation	**0.06** ***	(.021)	**0.09** ***	(.021)	**0.12** ***	(.022)	**0.10** ***	(.023)	0.04	(.028)
	HOME Material Environment	0	(.026)	**0.04** **	(.017)	0.01	(.017)	-0.01	(.022)	0	(.024)
	HOME Activities promoting development	0.02	(.02)	**0.04** **	(.017)	**0.06** ***	(.02)	0.03	(.02)	0.02	(.023)
	HOME Emotional Climate	**0.14** ***	(.028)	**0.07** ***	(.02)	**0.04** *	(.024)	0.02	(.023)	-0.04	(.027)
	HOME Promotion of Social Maturity	**0.06** ***	(.024)	**0.06** ***	(.021)	**0.08** ***	(.026)	**0.07** ***	(.023)	**0.07** **	(.03)
	HOME Materials and Experiences promoting development	**0.08** ***	(.023)	**0.08** ***	(.022)	**0.11** ***	(.019)	**0.10** ***	(.023)	0.03	(.027)
	Neighborhood Environment	-0.01	(.022)	0.01	(.025)	0.02	(.023)	0.03	(.024)	-0.01	(.028)
	Income	0.03	(.02)	0.02	(.019)	**0.04** *	(.019)	0.02	(.019)	0	(.026)
	Single Parenthood	0	(.031)	0	(.028)	0.02	(.024)	0.01	(.028)	0.01	(.032)
	Average Parental Age	-0.02	(.019)	-0.03	(.017)	0	(.016)	0.01	(.017)	**-0.06** ***	(.018)
	Number of Persons in Household	-0.04	(.025)	-0.03	(.024)	0.01	(.022)	0.03	(.027)	**0.05** **	(.025)
	Living with biological parents	**0.05** **	(.021)	**0.04** *	(.021)	**0.05** ***	(.014)	**0.04** *	(.021)	**0.04** *	(.027)
Number of components		3		3		3		3		3	
RMSECV		0.58		0.56		0.49		0.53		0.67	

Source: Mannheim Study of Children at Risk. 360 observations. Own calculations. Standard errors are in parentheses: ***significant at 1% level, ** significant at 5 % level, * significant at 10 % level. HOME items in *italics*

To sum up, the child functional levels can significantly be improved by avoiding organic risk. Autonomy is enhanced by the mother-child interaction. Play materials are strong predictors for functional levels just like they are for skills. Also the HOME subscore “avoidance of punishment and restriction”, single parenthood and living with biological parents can play a role. At the age of 8 years a multiplicity of patterns exists. Emotional climate seems particularly relevant for family and peer relationships, active stimulation and emotional and verbal responsivity are most important for the interests, school outcomes and peer relations and promotion of social maturity enhances all of the five functional levels.

6.5 Conclusion

The socio-emotional environment is crucial for life cycle skill formation. Even though it is known that early childhood shapes the development of cognitive and noncognitive skills to a great degree, there is still a research gap on how investments could ideally be designed at different ages. This paper therefore investigates the importance of multiple socio-economic conditions on cognitive, mental and emotional skill development. This could help to develop practical toolkits for educators and politicians.

Children are followed regarding their skills and environments from in utero conditions until adolescence in the Mannheim Study of Children at Risk (MARS). To measure investments the HOME score (Home Observation Measurement of the Environment) is employed. It consists of items measuring the quality of the home environment, such as the maternal involvement with the child, acceptance of the child, play materials, variety in daily stimulation and others.

This paper provides additional evidence to the existing literature by splitting up the HOME into several dimensions. The second novel feature is the consideration of multiple additional variables apart from the HOME that contain information on the birth risks, the mother-child interaction at the age of 3 months, breastfeeding, parental characteristics, income, the neighbourhood environment and others. Third, a PLSR (partial least squares regression) is presented that can deal with many correlated predictor variables.

In a first step, the aggregated HOME subscores are analysed, in a second step the HOME is divided into many different items. I find other environmental aspects apart from the HOME to be relevant for predicting skills of future periods - especially until the age of 4.5 years. During infancy the birth risks and the mother-child interaction outperform the HOME with respect to predictive power.

The results have several implications for policy makers and educators on how educational investments could be designed. The earliest investments should aim at avoiding birth risks. Organic risk factors could be reduced by policies that improve maternal health during pregnancy. Psychosocial risk factors could be addressed by providing assistance to pregnant mothers in their socio-economic environment. Organic risk has stronger adverse long-term effects relative to psychosocial risk, which is more detrimental for skills at the age of 2 years. Thus priority should be given to avoiding organic risk as the consequences of psychosocial risk can still be weakend by later investments. After birth, policies that help to improve the mother-child interaction are important. Breastfeeding seems to be advantageous, too. Even though early investments are crucial, they need to be complemented by later investments to produce high outcomes.

For cognitive skills parents, who actively support the child in training various tasks are important. This can be achieved by providing a stimulating material environment. It changes during childhood from toys that promote motor abilities to toys that teach shapes, colours, numbers and letters. In later childhood it refers to parents enabling the child to visit courses, to attend the library or to play a music instrument. The material environment may also include other related aspects that were not mentioned, but are linked to the same latent factor. If the family does not provide an adequate support, several of those factors could be substituted by policy makers.

For noncognitive skills a harmonious and motivational parent-child relationship is important. Reasonable investments tend to be linked to the emotional climate, the reasonable integration of the child in the household and the promotion of autonomy. Children that independently take over certain tasks in the household may indicate such a relationship.

My results suggest to favour the formation of cognitive skills first as they have a strong influence on mental skills and are likelier to yield positive long-term effects. During later childhood efforts should rather aim at improving noncognitive skills, because cognitive skills stabilize faster. Exceptions should be made for children, who have either particularly low cognitive or low noncognitive skills.

The relationship of investments and the child functional levels in the family, among peers, in school, regarding interests and the child's autonomy confirms the results. In particular, the autonomy of the child is rather driven by the infant environment. Conditions during later childhood can still significantly alter the child functional level in the family or among peers. School outcomes are more closely linked to the education of the parents, suggesting that parents who give more attention to education are relevant for their child's academic performance - apart from the HOME.

As the MARS still goes on, new variables that cover socioeconomic outcomes during adulthood could be regressed on a large set of environmental variables from birth until adolescence by PLSR in the future.

6.6 References for Chapter 6

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Eidesstattliche Erklärung

Ich versichere, dass ich die vorliegende Dissertation ohne Hilfe Dritter und ohne Benutzung anderer als der angegebenen Quellen und Hilfsmittel angefertigt habe. Diese Arbeit hat in gleicher oder ähnlicher Form noch keiner anderen Prüfungsbehörde vorgelegen.

- Karsten Reuß -