Age-dependent Skill Formation and Returns to Education

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Abstract:

In this study, we investigate the distribution of returns to investments in cognitive and selfregulatory skills over the life cycle. In our simulation model the distribution of returns to education results from the interaction of neurobiological and socio-economic 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 depriciation at older ages and calibrates it to German data. Our evidence quantitatively illustrates the shaping role early childhood has for human capital formation, inequality and growth.

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

JEL-classification: J21, J24, J31

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Acknowledgements:
Friedhelm Pfeiffer acknowledges financial support form the German Science Foundation under grants PF 331/2 ("Microeconometric Methods to Assess Heterogeneous Returns to Education") and PF 331/3 ("Wages, Rent-Sharing and Collective Wage Bargaining") and from the ZEW "Förderkreis". We would like to thank two anonymous referess, Anja Achtziger, Gunhild Berg, Kathrin Göggel, Michael Gebel, Peter Gollwitzer, Manfred Laucht, Matthias Mand, Christian Pfeifer and Winfried Pohlmeier, and seminar participants at the IAB workshop on work and fairness, the economic colloquium at the Technical University Darmstadt and the University of Dortmund for helpful discussions. All remaining errors are ours.

"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).

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 receives a great deal of attention. Early childhood shapes the formation of cognitive skills such as intelligence, memory power and reasoning as well as self-regulatory skills such as motivation, delay of gratification and social integration. The amount of these skills is decisive for becoming a productive member of the society. Feedback effects from the labour market are important to understand the investment processes and complex patterns of life cycle skill formation arise.

Reliable representative longitudinal data for analysing the returns on investments into cognitive and self-regulatory skills in early childhood is still rare (see the interpretation of the evidence by Cunha et al. 2006; severe deprivation in the first month of a newborn has long lasting negative impacts of 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 selfregulatory skill formation over the life cycle and a calibration of the model for a group of seven types of individuals with German data.

Our model is based on 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 are introduced, one for cognitive and one for self-regulatory skills, as well as age-specific skill deprecation rates. The parameters of the model are calibrated in a way that the simulated life cycle pattern of skills as well as human capital roughly fits 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 such that it replicates 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 its amount, time pattern and on differences in individual abilities. Institutional factors of the labour market that influence incentives and returns to educational investment and the distribution of wages are considered. Thus the paper deepens the empirical understanding of the returns on age-depending human capital investment over the life cycle, for growth and inequality.

The paper is organized as follows. The next part elaborates the ingredients of the simulation model of skill formation in detail. In part 3 the essential heterogeneity in skills and their formation over the life span as well as the calibration of the model parameters are introduced. Part 4 discusses findings from the simulated relationship between the technology of skill acquisition and the heterogeneity of returns to education over the life cycle. Part 5 concludes.

2. A Model of Skill and Human Capital Formation

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

There are two equations, one for cognitive, S_t^C, one for self-regulatory skills, S_t^N, that specify skill formation and depreciation on a yearly basis over the life span of 80 periods (years). Given an investment of the same amount a 70 year old presumably will not be able to enhance his skill level as much as a 5 year old, even though he 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 persons' learning aptitude, one for cognitive, l_t^C, and one for selfregulatory skills, l_t^N, respectively. The learning multipliers (figure 1) depend on age in a way that we regard as consistent with neurobiological and psychological findings from the child development literature (Duckworth 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 seem to have a higher degree of plasiticity in adolescence and across the life span. Therefore the self-regulatory learning multiplier is lower than the cognitive one in early childhood and becomes higher in early adolesence.

The basic structure of the equation for the development of skill *k* is:

$$S_t^k = \psi^k \cdot l_t^k \cdot \left\{ \frac{1}{3}(S_{t-1}^k)^\alpha + \frac{1}{3}(S_{t-1}^j)^\alpha + \frac{1}{3} \cdot \omega^k (I_t^k)^\alpha \right\}^{\frac{1}{\alpha}} + (1-\delta_{t-1}) \cdot S_{t-1}^k \qquad \text{with} \qquad S_t^k \geq 0 \qquad (1)$$

The first term represents skill formation as a CES production function (Cunha and Heckman 2007). Next period skills are produced by the level of both skills and by investments. α determines the degree of complementarity among skills and investment. ψ^k is an adjustment factor for the units to measure skills. ω^k represents an individual's ability to transform investments into skills and is set equal to one for a standard individual. We assume that each factor in the skill production function adds to the new skills with the same weight of 1/3 which seems to be in line with evidence provided by Cunha and Heckman (2008) for a production function similar to the first term of equation (1) (without the depreciation term). We tested the validity of our assumptions by computing six elasticities of investments on cognitive and self-regulatory skills to receive comparable values to the elasticities in Cunha and Heckman (2008), see Table 1 and 2. The elasticities from our simulation model do not differ significantly from the 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). Although the empirical evidence on these weights is still rare, we regard our assumptions as not implausible.

The second part of equation (1) models skill losses. Depreciation of skills is modest in childhood and accelerates with increasing age. Assuming a life expectancy *Le* of 80 years, the equation for the deprecviation process is:

$$\delta_t = \frac{1}{as \cdot (Le + 1 - t)} \qquad (2)$$

If as is larger than one, skill deprication is relatively low at the end of the life span. In the last period the individual loses all skills and dies. In our simulation we use *as*=5.85 (see part 3.1. below). In that case, equation (1) implies self-productivity ($\frac{\partial S_2^k}{\partial S_1^k} > 0$, this is true for $as > 1$) and direct complementarity ($\frac{\partial^2 S_t^k}{\partial I_t^k \partial S_{t-1}^j} > 0$) results 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 Achievement Scores and Human Capital

Another equation explains the achievement an individual can reach in performing a task as a result of her cognitive and selfregulatory skills. The two skills are both necessary and they may, in fact in rather complex ways, interact for measured achievement tests. A person with a high level of cognitive skills may produce low results, if she has only low motivation for participation. Several test procedures measure student performance in reading, mathematics or natural sciences (see for instance Weinert et al. 2001). We model the achievement with a Cobb Douglas function with equal weights of cognitive and selfregulatory skills[1]:

$$\mathrm{A}_t = \psi_A \cdot \sqrt{\mathrm{S}_t^C \cdot \mathrm{S}_t^N} \qquad (3)$$

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

The factor ψ_A is an adjustment factor for different levels of normalization of achievement scores and their distributions. We decided to calibrate our model to the PISA 2000 reading test score distribution for Germany, A_{16} (OECD 2000). In this distribution the ratio of the 90 to 10 percentil is 1.7 (= 620/363). In fact, the hetereogenity of skills might be higher in Germany so that this is a conservative assessment. For example, the ratio of the 90 to 10 percentil of consumption expenditures available for children until the age of six years in Germany (which should be regarded as an indicator of investment rather than skills) is 2.6 (10 344 € to 3 900 €, see Pfeiffer and Reuss 2008). Table 4 sums up the parameter variations that cause the PISA distribution on the basis of equation (3) for seven percentiles in three different scenarios.

Human capital in a given year is modelled as a function of cognitive and selfregulatory skills and of 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,

$$H_t = \psi_H \cdot \left({S_{t-1}^{C}}^{\gamma \cdot \frac{1}{3}} \cdot {S_{t-1}^{N}}^{\gamma \cdot \frac{1}{3}} \cdot {H_{t-1}}^{\gamma \cdot \frac{1}{3}} \right) + (1 - \delta_{t-1}^{H}) \cdot H_{t-1}. \tag{4}$$

Human capital depreciates according to $\delta_t^H = \theta_H \cdot \delta_t$, where θ_H is a parameter which may vary between individuals, jobs, industry or over time. A high value of θ_H will lead to an early human capital maximum (like in sports), a small θ_H to a later maximum (like in science). For the standard individual the average human capital maximum for Germany is used, figure 5 (t=52, see Franz 2006). The parameter γ determines the transformation of skills into human capital that depends on labour market charateristics. For $\gamma = 1$ the heterogeneity of skills is transformed into the heterogeneity of wages and human capital. For values greater than one the heterogeneity of wages exceeds the ones of skills (like in countries with large wage inequalities, for example Brazil or India) and for values smaller than one the reverse is true (like in a communist country).

3. Neurobiological and Socioeconomic Heterogeneity in Skill Formation

3.1. The "Standard" Individual

Cognitive and self-regulatory skills develop according to equation (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 $\alpha = 0$ and thus a Cobb Douglas function emerges for skill formation. The evidence of Cunha et al. (2007), 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 upon values between 0 and -0.2 do not change our conclusion much (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 $\alpha = 0$. *as* is adjusted in a way such that the value of $\mathrm{S}_{65}^{\mathrm{C}}$ in equation (1) is 87 percent of $\mathrm{S}_{20}^{\mathrm{C}}$ (that is, *as*=5.85). There is evidence in the literature that fluid problem solving decreases over the life cycle in a similar way (Kaufman et al. 1996 among others). For our standard individual cognitive skills start with a value of 180 ($S_0^C = 180$) which is 30 percent of the skills at the age of 20. This calibration is motivated from evidence of newborns brain volume which is about 25 to 30 percent of the brain volume in young adult age (Courchesne et al. 2000) and from evidence of information processing speed of four year old children which is about 35 percent of that of adults (Kail 2000). We do however not argue that there is a correlation between brain volume and cognitive skills, since skill formation over the life cycle depends on investments.

The standard individual, beginning at the age of 18, chooses the optimal amount of (symmetric) investment into the further development of his cognitive and selfregulatory skills in order to maximize his discounted lifetime human capital. The price of tertiary education is given to be 10 613 €

annually (this value equals the OECD 2007 calculation for per capita expenditures of tertiary education in Germany). Hence:

$$I_t^{k*} = \arg\max\left(\sum_{t=18}^{80}\frac{H_t - I_{t,i}^{C,N*}\cdot 10.613}{(1+i)^{t-18}}\right) \qquad (5)$$

Figure 2 shows the optimal 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 3. It replicates psychological findings on the development of cognitive skills and intelligence (see Courchesne et al. (2000), Caspi et al. (2005), West (2005)) and findings on the development of self-regulatory skills and social integration across 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 mid age. After an adjustment of ψ_A in (12) such that A_{16} equals 507.77 (the PISA reading test value in Germany for the 50th percentile (OECD (2000)), the achievement performance over the life cycle from equation (3) is illustrated in Figure 4. The decline of cognitive skills in later adulthood is compensated by rising self-regulatory skills, such that achievement remains high over the life span.

The average annual earnings of a fulltime worker in industries in Germany is 29 787 € (Federal Statistical Office Germany 2006). If we assume that an individual works from period 18 to period 65, lifetime earnings will be around 1,400,000 €. ψ_H in (4) is adjusted in a way so that this condition is satisfied. Furthermore ϑ^H in (4) is adjusted such that the human capital maximum is reached in t=52 (for empirical evidence for Germany see Franz 2006). The development of human capital across the life cycle for the standard individual is illustrated in figure 5.

3.2. A Population of Heterogeneous Individuals

For the purpose of calibrating, a population of seven heterogeneous individuals representing seven percentiles from 4,432 unique observations of the PISA 2000 (OECD 2000) reading test scores for

German students are used, see Table 3. Table 4 sums up the parameter variations that cause the PISA distribution on the basis of equation (3) for these seven percentiles and for three different types of (essential) heterogeneity:

- Heterogeneity stemming from differences in the amount of investments that indivuals receive from their socioeconomic environment from period 0 to 80.
- Heterogeneous ability to transform investments into new skills (given that individuals receive the same amount of investment).
- Heterogeneity in initial conditions, S_0^k, which may result for example from differences in utero conditions (in this case all individuals receive the same amount of investment and have the same ability to transform investments into new skills).

For instance, a student at the 99th percentile in the PISA test receives ceteris paribus skill investments that are 2.7684 times higher than those of the 50th percentile, defined as the "standard individual" (column 2). The individual learning ability of a student at the 99th percentile will be, ceteris paribus, 1.4 times as high as the one of the standard individual (column 3). Figure 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 too high.

The hetereogeneity in human capital is calibrated by the adjustment of γ and ψ_H in (4) to the empirical wage distribution in Germany (according to Gernandt and Pfeiffer 2007 the ratio of the 90 to the 10 percentile of the wage distribution roughly equals 3 in 2005). Inequality in human capital can result from inequality among skills at the age of 18, educational invesments during adulthood and differences in the characteristics of labour markets. Due to skill complementarity in the life cycle optimal investments into education in adulthood rise with the skill level.

4. Simulation Results

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 age of 18. The interest rate is assumed to be 2 percent. We calculate individual returns to education as the percentage change of the present value of the accumulated lifetime income in period 18 due to additional age-dependent investments in childhood.

It can be argued that an exogenous increase in investments (for example by the government) may cause families to reduce their investments so that crowding out takes place. Crowding out of government investments depends mainly on socioeconomic patterns and the design of an intervention. There will be only little crowding out an intervention is not anticipated and if additional investments complement present investments and vice versa (see Das et al. 2004, Hong-Kyun 2001, among others). Investments often increase the resources of a mother, 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 potential optimally designed investments can have depending on age. The optimal design is a different issue.

We define investment impulses that provides an additional investment ($I_t^k = 5, k = C, N$) from the age of 0 until 5, called preschool investment impulse, from period 6 to 11 (primary impulse), from period 12 to 17 (secondary impulse) and a tertiary impulse lasting from 18 to 21. The tertiary educational impulse is specific in the sense that individuals have to sacrifice four years of income in order to attend this education. The Euro cost of an annual investment impulse is 5 627 (the cost per head in the German educational system in 2005 repropted in OECD 2007).

Table 5 reports the resulting returns on investments for 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 will profit less from an additional investment impulse in terms of additional absolute monetary earnings (see Table 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 from bright environments. However, the relative gains (the additional earnings in percent of actual earnings) are significantly higher for individuals from disadvantaged environments (see Table 5). This is due to decreasing marginal rates of return to additional investments if only one exogeneous factor in the skill production function is enhanced while the others remaining 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 age increasing, 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 smaller than the costs, because the low skill level cannot completement investment in young adult age. 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 is the level of skills still small enough to generate a high individual rate of return.

Table 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 heteorgenity type two, our individuals do not differ with respect to their environment and investment. Decreasing marginal rates of education do not play a role in this scenario since the population of the seven individuals receives absolutely identical amounts of inputs from their environment. 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 stemming from the environment. This is a result of the property of self-productivity in the technology of skill formation. These findings have important implications for compensating policies. If the source of heterogeneity results from different abilities instead of different environments it follows that for successful compensating policies more resources will be needed.

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

4.2. Individual Giftedness and Social Environment

Presumably heterogeneity stemming from different environments and abilities will arise simultaneously (Heckman 2007, Weinert 2001). To assess rates of returns for this case we study a model variant with a population of individuals, whose heterogeneity of skills is explained by environment and giftedness each with 50 percent. The new population consists of 49 heterogeneous individuals reflecting all possible combinations of environmental and giftedness variations. Table 7 depicts the absolute monetary as well as 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 who received the highest investments in their social environment. However, the highest individual returns to an educational impulse are achieved by individuals with a high giftedness coming from disadvantaged environments.

4.3. Optimal Duration of Tertiary Education

Next we investigate the decision of choosing the optimal duration of tertiary education. Individuals maximize their returns on investment considering the trade off between higher lifetime earnings caused by additional skill formation and its costs. Table 8 summarizes the results. Two factors drive the decision of how long to attend university. First, gifted students will accumulate skills more easily starting already in early childhood and thus perceive a higher benefit from attending tertiary education. Secondly, students from more favourable environments achieve higher gains from attending university. Hence highly gifted students from favourable environments tend to remain in university for the longest time even though facing the highest opportunity cost. Less gifted inividuals from unfavourable environments who have accumulated less human capital and thus have a lower opportunity cost will invest less in their tertitary education. This is due to a smller educational benefit because of skill complementarity effects and the higher education costs.

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 adjust wage inequality to the level of three different countries whereas the inequality of skills remins the same. Hence we assume that the degree of inequalities in wages is caused by differences in labour markets. The first country has a 90-10 ratio of 1.89 and thus a relatively small wage inequality (like for instance Norway), the second country has a 90-10 ratio of 3 like in Germany and the third country a relatively high inequality in earnings with a 90-10 ratio of 7 (higher than in the United States and lower than in India).

For a 90-10 income ratio of 7 the average optimal adult life investment increases significantly compared to the medium case. For the 10th percentile it is now 0.11, for the median 0.28, and 0.5 for the 90th percentile. The numbers in Table 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 10 contains the individual rates of return from the preschool impulse for the three countries. The numbers suggest that rising labour market inequality increases the returns on investments to education significantly. The incentive to invest in additional education rises when people enter labour markets with a higher skill premium.

5. Concluding Remarks

Our simulation based evidence illustrates the shaping role early childhood has for human capital formation, growth and inequality. Our life cycle model is adjusted in a way that it captures human capital formation in Germany. A framework is presented which allows 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 higher than for self-regulatory skills. The second type of (essential) heterogeneity in skill fromation stems from different amount of investments into skills provided by the family or the socio-economic environments. The third type of heterogeneity results from individual differences in the ability to transform an educational investment into additional skills.

We compare absolute and relative rates of returns for a population of seven individuals for an additional investment in early childhood and in primary, secondary and tertiary education. The rates of return are assessed over the period from age 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 into cognitive as well as into self-regulatory skills until they reach early adolescence. Even though investment in cognitive skills at an early stage seems more important than investing into self-regulary skills, both investments complement each other and are both necessary. In later adolescence age investments into self-regulatory are more profitable. Individual incentives to invest in education (after the age of 18) rise with wage inequality.

Furthermore, differences in individual giftedness have a higher impact on inequality than differences stemming from the environment. If heterogeneity stems from the individual ability of transforming educational inputs into new skills (and not from socio-economic differences of families and the environment), 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 educational policies face that are designed to reduce inequality.

In future research, improved longitudinal and cross-section data, both experimental and non-experimental, needs to be collected to upgrade the empirical understanding of the cumulative and synergetic nature of age-dependend skill formation and the way families, schools and policies shape the future workforce, growth and inequality.

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Figures

Figure 1: Learning multipliers (illustrated from age 0 to 50)

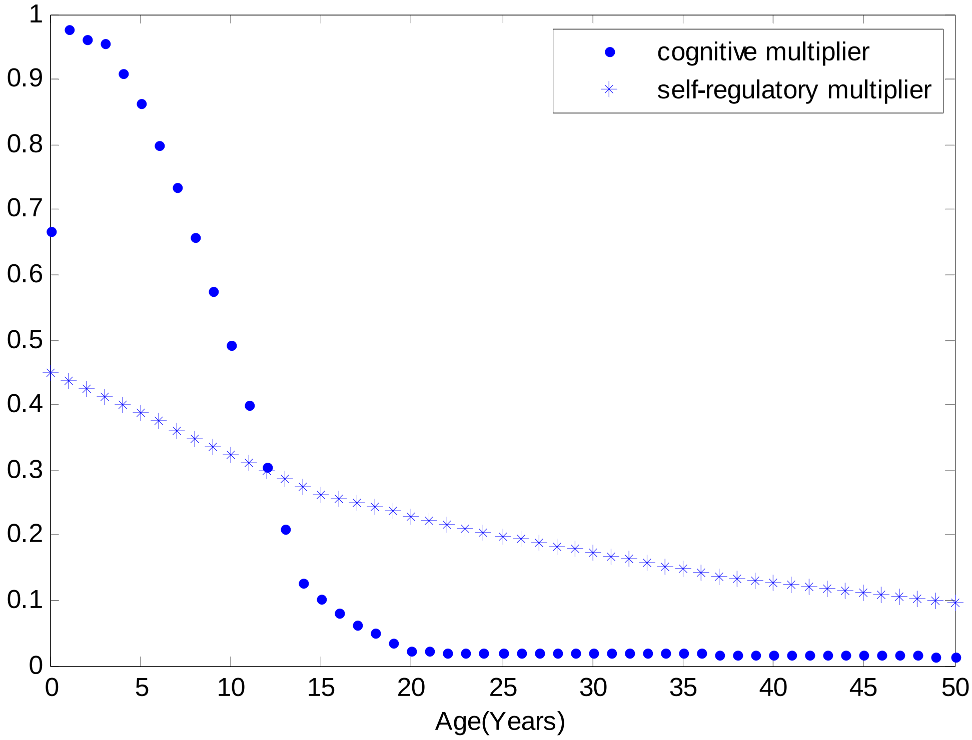


Figure 2: Optimised investments in skills during adulthood

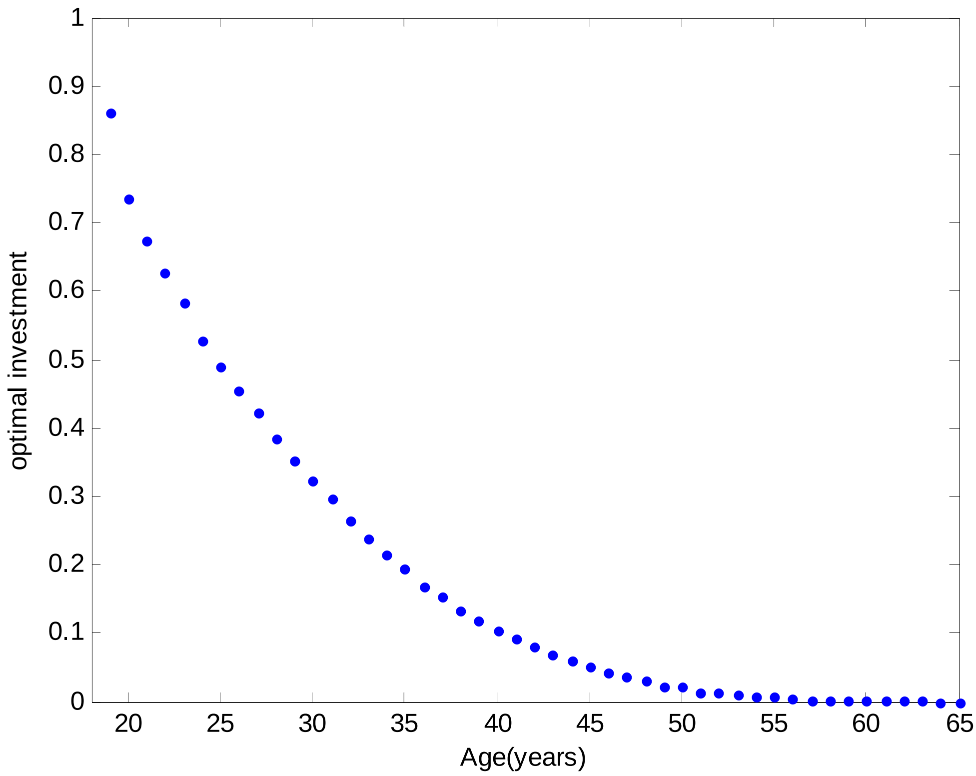


Figure 3: Skill development from age 0 to 80

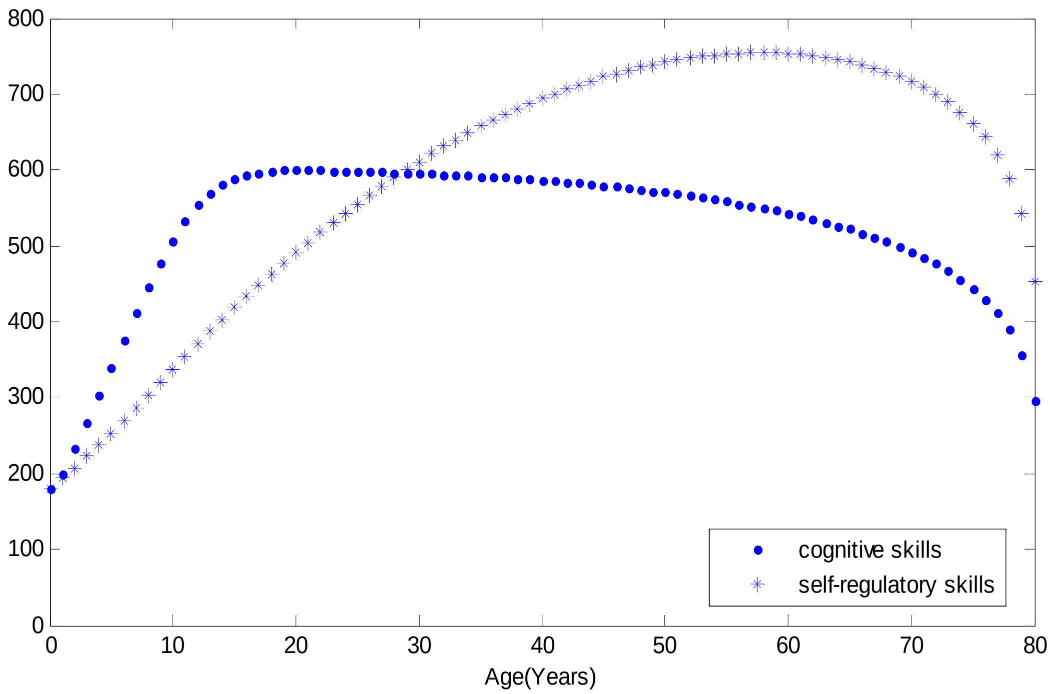


Figure 4: Achievement scores from age 0 to 80

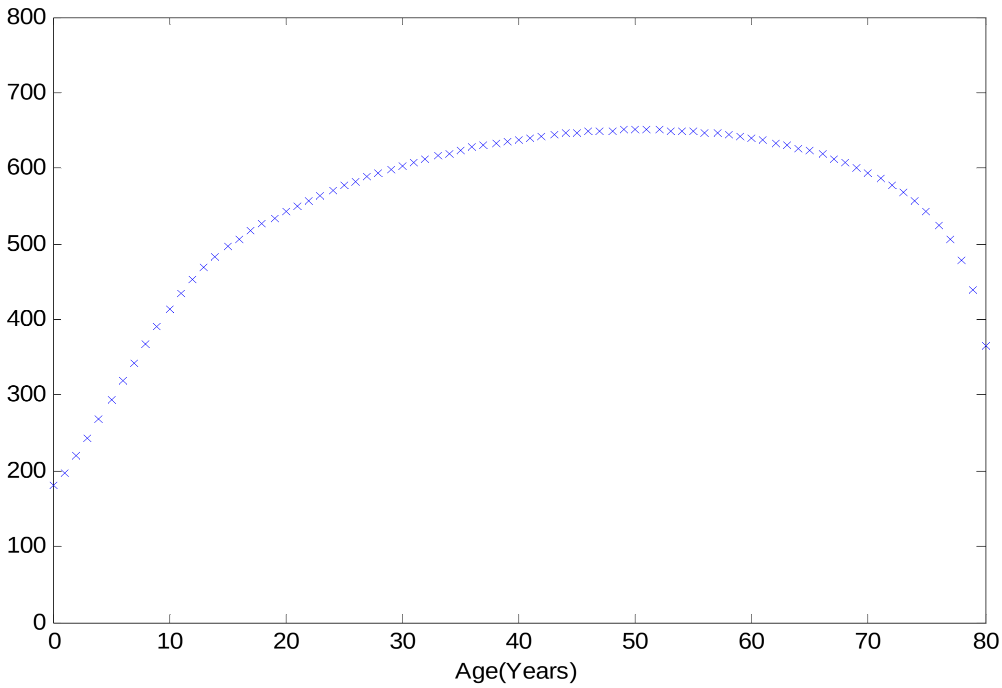


Figure 5: Human capital over the life cycle

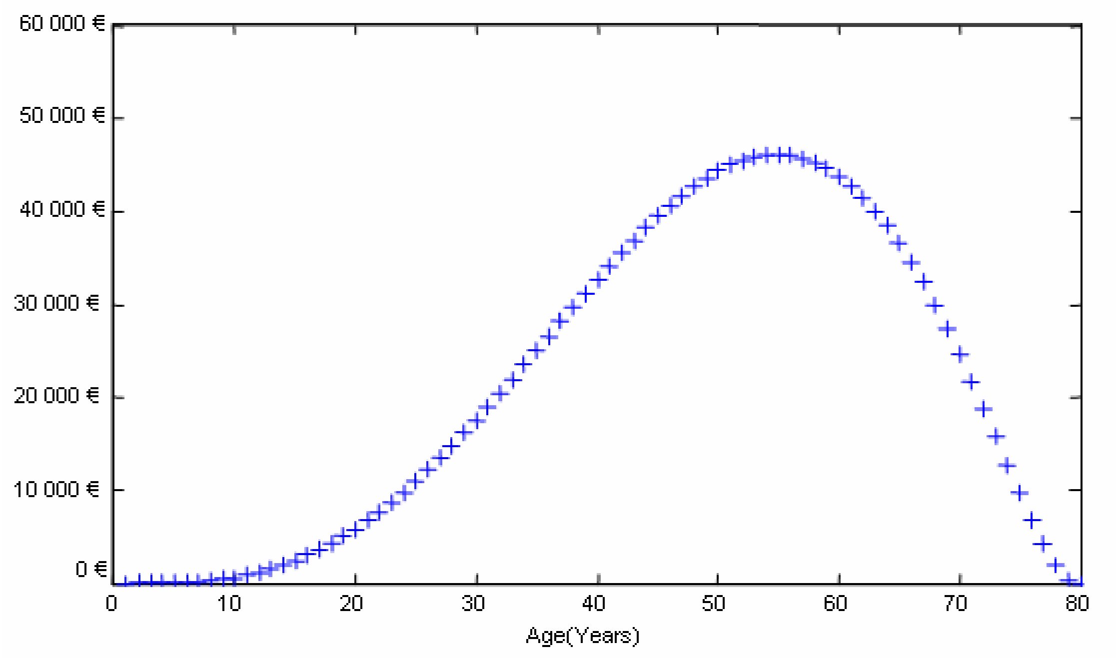
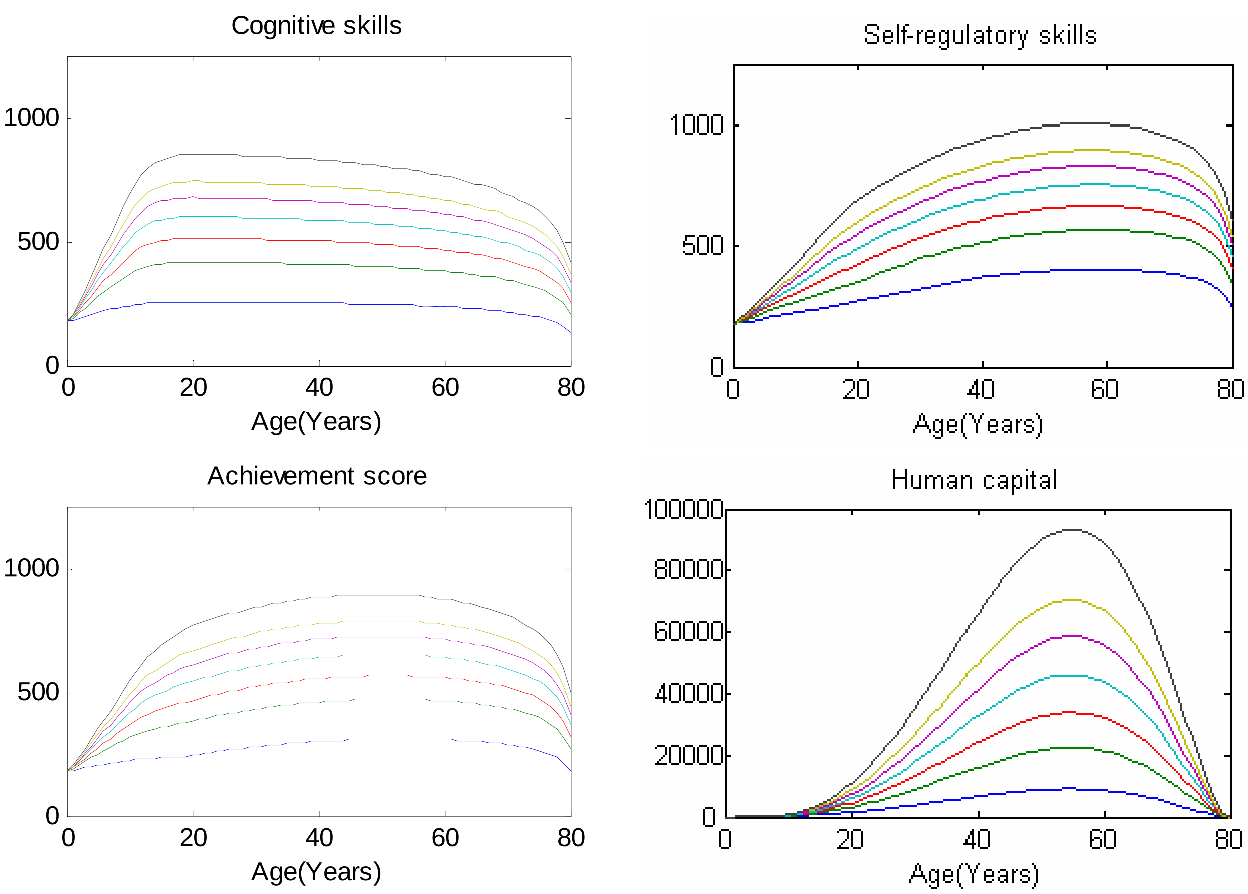


Figure 6: A population of seven individuals with heterogeneous environments



Tables

Table 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: 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 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 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 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 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 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 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 9: Discounted lifetime earnings in Euros for countries differing in wage inequality

Percentile	90-10 ratio:1.89	90-10 ratio:3	90-10 ratio: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 10: Individual rates of return for a preschool impulse with a duration of 6 years

Percentile	90-10 ratio : 1.89	90-10 ratio : 3	90-10 ratio : 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%