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ABSTRACT

Age-Dependent Skill Formation and Returns to Education: Simulation Based Evidence*

This study integrates findings from neurobiology and psychology on early childhood development and self-regulation to assess returns to education. Our framework for evaluating the distribution of age-specific returns to investments in cognitive and noncognitive skills is a lifecycle simulation model based on the technology of skill formation (Cunha and Heckman (2007)). Our findings illustrate the cumulative and synergetic nature of skill formation, the skill multiplier, and the shaping role early childhood has for human capital formation, growth and inequality.

JEL Classification: J21, J24, J31

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

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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).

1 Introduction

Multiple skills are required for the formation of human capital. Cognitive skills such as intelligence, memory power and reasoning as well as noncognitive skills such as self-regulation, persistence and social integration constitute human capital. The formation of skills is a cumulative, synergetic process which is affected by the environment, genetic endowments, and both formal and informal investments in education. Since “skills beget skills” (Cunha et al. (2006, p.702)), skill formation in early childhood will have lasting effects for the development of intelligence and self-regulation as well as for student achievement scores, socio-economic success and human capital (see Cunha and Heckman (2007), Heckman et al. (2006), Heckhausen and Heckhausen (2006)).

Since reliable representative longitudinal data that allow an empirical assessment of the quantitative role of investments in cognitive and self-regulatory skills in early childhood for human capital accumulation (called the skill multiplier by Heckman (2007), see the competent summary of research on intervention programs for disadvantaged children by Cunha et al. (2006)) are still rare, our contribution to the literature is simulation based evidence. We are specifically interested in illustrating the meaning of early childhood as a sensitive period of human capital formation. Our framework for assessing the distribution of age-specific returns to investment in skills is a lifecycle simulation model based on ideas presented by Cunha and Heckman (2007). The model is capable of illustrating the relationship between individual heterogeneity, investments in skills, sensitive periods in skill formation, and the resulting heterogeneous returns to age-specific investments in skills.

Our model takes into account the changing nature of skill formation over the life span and the interdependency between cognitive and self-regulatory (noncognitive) skills. More precisely, significant differences are modelled between skill formation both in early and later childhood and adolescence. On the one hand, the formation of a standard investment impulse in skills is the more productive the earlier in life it takes place. On the other hand, depreciation processes become quantitatively more important later on in life. In our model, the formation of skills in a certain period depends on the acquired skills from earlier periods and current investments. We simulate skill production functions with the characteristics of self-productivity and direct complementarities. The two concepts formalize some basic features of the nature of learning and skill formation (Cunha and Heckman (2007)):

1. Self-productivity (or recursive productivity): Skills of past periods remain productive for the attainment of current skills.
2. Direct skill complementarity: The higher the skill level the more productive may the return of subsequent investments in skills be.

Since skills are multiple by their nature, the technology of skill formation is multidimensional. In our model, the multidimensionality of skills is reduced to the two dimensions of cognitive and self-regulatory skills. The simulation model consists of four different equations which will briefly be sketched. The interactions among cognitive and self-regulatory skills and investments in these skills are modelled by a system of two interrelated production functions. The processes of depreciation of skills as well as aging are integrated into the simulation model. Additional heterogeneity of individuals stems from different family and social environments, different individual learning abilities, and different degrees of complementarities between cognitive and self-regulatory skills in the production functions.

Heterogeneity of cognitive and self-regulatory skills is adjusted in a way such that their interaction generates the distribution of the PISA 2000 achievement scores in reading of 16 year old German students. The value of human capital of a standard simulated individual is adjusted such that it is equal to the value of an average German worker from the industry. The inequality of human capital is not only influenced by the heterogeneity of skills. Differences in individual mobility, labour markets and their institutions will transform skills into human capital and wages as well. The heterogeneity of human capital is adjusted in a way such that it approximates the 90-10 percentile ratio of wages in Germany.

With these adjustments we utilize the model

- to assess the distribution of returns to symmetric investments in both types of skills in different phases during child- and adulthood (pre-school, primary, secondary and post-secondary education),
- to highlight the role of complementarities between cognitive and self-regulatory skills for the returns to education,
- to compare the role of socio-economic family backgrounds and individual differences in learning capacities for the heterogeneity of returns to education, and
- to contribute to the understanding of policies to foster human capital and growth and its distribution in the society.

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

2. A Simulation of a Model of Skill and Human Capital Formation

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

Cunha and Heckman (2007) provide the starting point for the development of the technology of skill formation across the life span. We create an enhanced system of two equations, one for cognitive, S_t^C, and one for self-regulatory skills, S_t^N, that specifies skill formation and depreciation on a yearly basis over eighty years. The basic structure of the equation for skill *k* is:

$$S_t^k = learning_t^k + S_{t-1}^k - losing_t^k \tag{1}$$

On average, a young child learns easily even though the level of skills is still low. An older person, on the other hand, managed to collect a high level of skills, but doesn't learn as fast as the young child. In order to model these differences, we add two learning multipliers determining the persons' learning aptitude, one for cognitive, $\mathrm{l}_\mathrm{t}^\mathrm{C}$, and one for noncognitive skills, $\mathrm{l}_\mathrm{t}^\mathrm{N}$, respectively. The learning multipliers depend on age in a way that we regard as consisted with neurobiological and psychological findings from the child development literature (Oerter and. Montada (2002)), see Figure 1. We assume that the noncognitive learning multiplier is lower than the cognitive learning multiplier in early childhood and becomes higher in early adolescence.

Equations 2 and 3 represent the relationship between cognitive and noncognitive skills as the relevant outputs over the life span and educational and environmental inputs. For illustrative reasons it is assumed that the stock of cognitive and noncognitive skills as well as the investments, all contribute with an equal weight of 1/3 to the formation of new skills.

$$learning_t^C = \psi^C l_t^C \left\{ \frac{1}{3}(S_{t-1}^C)^\alpha + \frac{1}{3}(S_{t-1}^N)^\alpha + \frac{1}{3}\delta(I_t^C)^\alpha \right\}^{\frac{1}{\alpha}} \tag{2}$$

$$learning_t^N = \psi^N l_t^N \left\{ \frac{1}{3}(S_{t-1}^C)^\alpha + \frac{1}{3}(S_{t-1}^N)^\alpha + \frac{1}{3}\delta(I_t^N)^\alpha \right\}^{\frac{1}{\alpha}} \tag{3}$$

α determines the degree of complementarities between cognitive and self-regulatory skills and ψ^C and ψ^N are some adjustment factors for the units to measure skills. δ represents an individual's ability to transform investments into skills and is set equal to one for an average individual. Depreciation of skills accelerates with increasing age. Let v_t be the number of periods needed until a person will loose all his skills completely given that no new investment takes place. Let $v_t^C = v_t^N = v_t$. Furthermore it is assumed that $\frac{\partial v_t}{\partial t} < 0$ and $\frac{\partial^2 v_t}{\partial^2 t} = 0$. The loss of skills increases with age, but the decrease in the loss of v_t is assumed to be constant. Let *as* be the speed of aging within each period and let *Le* be life expectancy. *Le* is defined as the number of periods needed until $v_t = 0$, defined as the time when the individual loses all its skills (which may be interpreted as the death of this individual). For simplification we assume that *Le=80* for all individuals in our simulation. This parameter will be changed for investigating its relevance for investments in skills. These assumptions lead to the following function for v_t :

$$v_t = as \cdot (Le - t) \tag{4}$$

For the starting period this implies: $v_0 = as \cdot Le$.

If v_t is the amount of time it takes to depreciate the skill level to zero, annual depreciation will be:

$$losing_t^C = \frac{S_{t-1}^C}{as \cdot [Le - (t-1)]} \tag{5}$$

and

$$losing_t^N = \frac{S_{t-1}^N}{as \cdot [Le - (t-1)]} \tag{6}$$

By substituting (2) and (5) into (1), one obtains equation 7 for cognitive skills:

$$S_t^C = \psi^C \cdot l_t^C \cdot \left\{ \frac{1}{3}(S_{t-1}^C)^\alpha + \frac{1}{3}(S_{t-1}^N)^\alpha + \frac{1}{3} \cdot \delta \cdot (I_t^C)^\alpha \right\}^{\frac{1}{\alpha}} + S_{t-1}^C - \frac{S_{t-1}^C}{as \cdot [Le - (t-1)]} \tag{7}$$

and equation 8 for self-regulatory (non-cognitive skills):

$$S_t^N = \psi^N \cdot l_t^N \cdot \left\{ \frac{1}{3}(S_{t-1}^C)^\alpha + \frac{1}{3}(S_{t-1}^N)^\alpha + \frac{1}{3} \cdot \delta \cdot (I_t^N)^\alpha \right\}^{\frac{1}{\alpha}} + S_{t-1}^N - \frac{S_{t-1}^N}{as \cdot [Le - (t-1)]} \quad (8)$$

Self-productivity ($\frac{\partial S_2^k}{\partial S_1^k} > 0$) for cognitive skills implies:

$$\frac{\partial S_t^C}{\partial S_{t-1}^C} = 1 + 3^{-(1/\alpha)} \cdot \psi^C \cdot l_t^C \cdot S_{t-1}^{C\,(-1/\alpha)} \cdot (\delta \cdot I_t^{C\alpha} + S_{t-1}^{C\;\alpha} + S_{t-1}^{N\;\alpha})^{-1+(1/\alpha)} - \frac{1}{as + as \cdot (Le - t)} > 0 \quad (9)$$

$$\Leftrightarrow 1 + 3^{-(1/\alpha)} \cdot \psi^C \cdot l_t^C \cdot S_{t-1}^{C\,(-1/\alpha)} \cdot (\delta \cdot I_t^{C\alpha} + S_{t-1}^{C\;\alpha} + S_{t-1}^{N\;\alpha})^{-1+(1/\alpha)} > \frac{1}{as + as \cdot (Le - t)}.$$

And self-productivity for noncognitive skills implies:

$$\frac{\partial S_t^N}{\partial S_{t-1}^N} = 1 + 3^{-(1/\alpha)} \cdot \psi^N \cdot l_t^N \cdot S_{t-1}^{N\,(-1/\alpha)} \cdot (\delta \cdot I_t^{N\alpha} + S_{t-1}^{C\;\alpha} + S_{t-1}^{N\;\alpha})^{-1+(1/\alpha)} - \frac{1}{as + as \cdot (Le - t)} > 0. \quad (10)$$

For equation (9) the term $3^{-(1/\alpha)} \cdot \psi^C \cdot l_t^C \cdot S_{t-1}^{C\,(-1/\alpha)} \cdot (\delta \cdot I_t^{C\alpha} + S_{t-1}^{C\;\alpha} + S_{t-1}^{N\;\alpha})^{-1+(1/\alpha)}$ is always greater than zero. Thus, as long as $\frac{1}{as + as \cdot (Le - t)}$ is greater than 1 across the whole life span, skill formation can be characterised by self-productivity. This is satisfied for most values except for very small as and very large t. Even for t=80 self-productivity will be satisfied as long as $as > 1$. In the simulation model, we use *as*=5.85 (see chapter 3.1.). Condition (9) is therefore always satisfied and (10) analogously.

The degree of complementarities of skill l for the production of skill k is given by $\frac{\partial^2 S_t^k}{\partial I_{t-1}^k \partial S_{t-1}^l} > 0$.

By using equations (7) and (8) it follows:

$$\frac{\partial^2 S_t^C}{\partial I_t^C \partial S_{t-1}^N} = \underbrace{\frac{1}{9} \cdot I_t^{C\,-1+\alpha} \cdot \psi^C \cdot l_t^C \cdot S_{t-1}^{N\;-1+\alpha} \cdot \left(\frac{I_t^{C\alpha} \cdot \delta}{3} + \frac{S_{t-1}^{C\;\alpha}}{3} + \frac{S_{t-1}^{N\;\alpha}}{3} \right)^{-2+(1/\alpha)}}_{>0} \cdot \underbrace{(-1 + \frac{1}{\alpha}) \cdot \alpha \cdot \delta}_{>0} > 0 \quad (11)$$

It is easy to show that (11) is always true as long as $\alpha < 1$ that is as long as there is no full substitutionality. The first part cannot be negative as long as the learning multiplier, investments, and the level of skills are positive. For $1 > \alpha > 0$ the second part contains two positive factors being multiplied. For $\alpha < 0$ two negative factors multiply to a positive product. Thus, the product cannot turn negative. Vice versa the same is true for $\frac{\partial^2 S_t^N}{\partial I_t^N \partial S_{t-1}^C}$ since the only differences of equation (8) compared to (7) are the terms ψ^N and l_{t-1}^N which are always greater than zero just like ψ^C and l_{t-1}^C .

2.2 Achievement Scores and Human Capital

The third equation explains the achievement that an individual can reach in performing a task as a result of her cognitive and self-regulatory 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 performances in reading, mathematics or natural sciences (see for instance Weinert (2001)). In our model, the achievement score of PISA 2000 for Germany, A_t , is "produced" in each period by a Cobb Douglas function with equal weights for cognitive and non-cognitive skills:

$$\mathrm{A}_t = \psi_\mathrm{A} \cdot \sqrt{\mathrm{S}_t^\mathrm{C} \cdot \mathrm{S}_t^\mathrm{N}} \tag{12}$$

The factor ψ_A is an adjustment factor for different levels of normalization of achievement scores and their distributions. The PISA 2000 reading test score has been obtained at the age of sixteen, A_{16} .

Human capital in a given year is modelled as a function of cognitive and self-regulatory 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,

$$H_t = accumulation_t^H + H_{t-1} - depreciation_t^H \tag{13}$$

For reasons of simplicity we assume a Cobb Douglas production function for the accumulation process where each of the three factors has the same elasticity. The sum of the elasticities may vary with the parameter γ and we will investigate the consequences for the distribution of the returns to education from varying values of γ below. For high values of γ, large differences in skills will enhance differences in human capital. A small γ, on the other side, will lead to a smaller variation of human capital. For $\gamma = 0$, human capital is the same for all skill levels. Thus,

$$accumulation_t^H = \psi_H \cdot \left({S_{t-1}^C}^{\gamma \cdot \frac{1}{3}} \cdot {S_{t-1}^N}^{\gamma \cdot \frac{1}{3}} \cdot {H_{t-1}}^{\gamma \cdot \frac{1}{3}} \right). \tag{14}$$

Human capital is expressed in the dimension EURO. This may be interpreted in a way that individuals get paid according to the value of their human capital. Let ψ_H be the adjustment factor transforming skills and the stock of human capital into EUROs. Furthermore, a function is needed for the depreciation of human capital across the life span. This is modelled analogously to skill loss.

$$v_t^H = \vartheta^H \cdot v_t = \vartheta^H \cdot as \cdot (Le - t) \tag{15}$$

ϑ^H is the depreciation factor which may vary between individuals, jobs, industries, and over time. For example, a higher ϑ^H will lead to an earlier human capital maximum in a job or an industry, a lower ϑ^H to a maximum later on. For some activities like soccer, the maximum is reached early in life, but for others like philosophers the maximum may be reached later on. Thus,

$$depreciation_t^H = \frac{H_{t-1}}{v_{t-1}^H}. \tag{16}$$

Inserting (15) in (16) and (16) together with (14) in (13), the full human capital equation is:

$$H_t = \psi_H \cdot \left({S_{t-1}^C}^{\gamma \cdot \frac{1}{3}} \cdot {S_{t-1}^N}^{\gamma \cdot \frac{1}{3}} \cdot {H_{t-1}}^{\gamma \cdot \frac{1}{3}} \right) + H_{t-1} - \frac{H_{t-1}}{\vartheta^H \cdot as \cdot (Le - t + 1)} \tag{17}$$

3. Creating Heterogeneity in Skill Formation

3.1. The "Standard" Individual

The cognitive and self-regulatory skills of a standard individual are the results of equations (7) and (8) which interact for 80 periods. ψ^k with $k=C, N$ is adjusted so that the level of cognitive skills at the age of 20 is $S_{20}^{C} = 600$ for all types of complementarities. A standard individual is furthermore defined with $\alpha = 0$. In this case, the CES function collapses to a Cobb Douglas production function for skills (for more details see Pfeiffer and Reuß (2007)). Following results of Kaufman et al. (1996), the adjusted mean of the fluid problem solving score of a 65 year old is equal to 87 percent of the adjusted mean for 20 year old individuals, which is equal to $\mathrm{S}_{20}^{\mathrm{C}}$ (or 600).

as is adjusted in a way such that the value of $\mathrm{S}_{65}^{\mathrm{C}}$ in equation (7) is 87 percent of the value of $\mathrm{S}_{20}^{\mathrm{C}}$, which is 5.85. For a newborn, the size of the brain is equal to about 25 to 30 percent of the brain value at young adult age (Courchesne et al. (2000)). We assume S_0^C to be 30 percent of S_{20}^C, hence we set $S_0^C = 180$. Furthermore, each year the standard individual will invest one unit in both skills during its whole life which implies that $I_t^k = 1$.

For the standard individual, the level of cognitive and self-regulatory skills over the life cycle is illustrated in Figure 2. It replicates psychological findings on the development of cognitive skills and intelligence ((see Courchesne et al. (2000), Caspi et al. (2005), Kliegel and Jäger (2006), 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 50$^{\text{th}}$ percentile (OECD (2000)), the achievement performance over the life cycle from equation

(12) is illustrated in Figure 3. Achievement captures the compensation of declining cognitive skills on the one hand and the effect that rising self-regulatory skills might have during mid adult age on the other hand.

The average annual income of a fulltime worker in industries in Germany is 29,787 Euros (Statistisches Bundesamt (2006)). If we assume that an individual works from period 18 to period 65, her lifetime earnings will be around 1,400,000 Euros in nominal terms. ψ_H in (17) is adjusted in a way so that this condition is satisfied. For standardization issues, ϑ^H in (17) is always adjusted such that the human capital maximum is reached in t=55 (for empirical evidence see Franz (2006)). Given theses adjustments, the development of human capital across the life cycle for the standard individual is illustrated in Figure 4.

3.2. Creating Heterogeneity in Skill Formation

For the purpose of calibrating our simulation model, we use 4,432 unique observations from the PISA 2000 (OECD (2000)) reading test scores for German students. From these observations, we derive seven percentiles of the scores of reading performances (Table 1). Table 2 summarizes the parameter variations causing the PISA distribution on the basis of equation 12 for seven percentiles. Three different scenarios are assumed.

a) Heterogeneity in investments from period 0 to 80. This can be the case if individuals live in different environments that persist throughout lifetime.

b) Heterogeneous ability to acquire skills. Now all individuals receive the same investment, but they differ persistentently in their ability to transform investment into skills.

c) Heterogeneous starting conditions. Individuals all have the same investment and the same ability to acquire skills, but start with different skill values, S_0^k, which may result for instance due to in utero conditions.

In different simulation models, the parameters of essential heterogeneity in the two basic skill production functions are chosen such that they generate the PISA distribution according to equation 14 at the age of sixteen (see Table 2). 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 5 illustrates the level of cognitive and self-regulatory skills, achievement, and human capital for the population of heterogeneous skill investments during childhood on an annual basis. To find a reasonable value for complementarities, simulations have been performed for different values of α. In all variants of the model an adjustment of ψ^k for *k=C, N* guarantees that $S_{20}^k = 600$ for all complementarities. This adjustment is necessary since different values for α cause numerical differences in the CES production function $learning_t^k$, but leave $losing_t^k$ basically unchanged.

It turned out that for high complementarities, the environment is more important than starting conditions and vice versa (see Pfeiffer and Reuss (2007)). The results furthermore indicate that the Cobb Douglas case ($\alpha = 0$) seems to be a reasonable model of the synergetic nature of learning with multiple inputs in the case of Germany. Therefore, in the following we will proceed with the assumption $\alpha = 0$. We also model how the labour market transforms educational heterogeneity into income heterogeneity. By an adjustment of γ and ψ_H in (17) the model can be calibrated to any empirical wage distribution. To adjust our simulation results to the German labour market, we use the 90-10 ratio of inequality in earnings which roughly equals 3 (Gernandt und Pfeiffer (2006), OECD (2006a)). Thus, inequality in human capital is a result of the inequality of skills and of differences in labour markets.

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 while accumulating earnings. The amount of human capital of each individual is defined as the present value of the sum of annual earnings evaluated at age of 18. The interest rate is assumed to be 2 percent. Individual returns to education will be measured by the percentage change of the present value of the accumulated lifetime income in period 18 due to additional age-dependent educational investments.

We define a preschool investment impulse which provides an additional constant skill investment ($I_t^k = 5, k = c, n$) from the age of 0 until 5, a primary impulse from period 6 to 11, a secondary school impulse from period 12 to 17, and a tertiary educational impulse lasting form 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 given by 5,627 € which is equal to the estimated average of educational investments per student in Germany in the year 2005 (OECD (2006b)). In our model, we assume that an individual has to pay 5,627 € per annum for this educational impulse.

Table 3 shows the resulting returns to education. Higher learning multipliers l_t^k in young age and the cumulative nature of skill formation due to self-productivity and direct complementarities make early skill investments more profitable, in line with Cunha and Heckman (2007). 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 (Table 3). Thus, it follows 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 (Table 3). This is due to decreasing marginal rates of return to additional investments if only one factor in the CES production function is enhanced while the others remain constant.

Individuals with a higher skill level will benefit relatively less from additional investments. This surpasses the positive effect of skill complementary on individual rates of return. Thus, if society is interested in maximizing the relative gains in earnings and 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 and thus, has 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 in order to generate a high individual rate of return.

Table 4 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, δ. For this case, 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 for the returns to age-dependent education differ from the previous ones, see Table 4.

The absolute and relative returns to education 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 inequality than differences stemming from the environment. This is a result of the property of self-productivity in the technology of skill formation. Obviously, these findings may have important implications for compensating policies. If the sources of heterogeneity are varying individual abilities to transform educational inputs into new additional skills instead of varying 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 (see Heckman (2000, 2007)).

4.2. Individual Giftedness and Social Environment

Presumably, heterogeneity arising from different environments and abilities will arise simultaneously. In order to assess the rates of returns for this case, we study a model variant with a population of individuals where 50 percent of the heterogeneity of skills is explained by the environment and 50 percent by giftedness. The population consists of 49 heterogeneous individuals reflecting all possible combinations of environmental and giftedness variations. Table 5 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 education 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 will maximize their returns to education by considering the trade off between higher lifetime earnings caused by additional skill formation and its costs. Table 6 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 receive a higher benefit from attending tertiary education. Secondly, students from more favourable environments achieve higher gains from attending university. They tend to remain in university for a longer time even though facing the opportunity cost of not being able to work during this time.

4.4. Wage Inequality and Returns to Education

In this part, we consider the relationship between wage inequality and the returns to education which has been intensely researched in recent years (see for instance Acemoglu (2002)). We assume heterogeneous skills due to heterogeneous family environments and adjust wage inequality to the level of three different countries. Educational levels in these countries are calibrated to the German PISA 2000 reading results. That is, we assume that the degree of inequalities in wages is caused by differences in labour markets and not by differences in skills. 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).

The numbers in Table 7 illustrate the differences in human capital arising from the modelled labour market institutions given that the heterogeneity of skills is the same in each country. Table 8 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 to education significantly. The incentive to invest in additional education rises when people plan to enter a labour market with a high skill premium.

5. Concluding Remarks

Our simulation based evidence illustrates the understanding of the skill multiplier (see Cunha and Heckman (2007)) and the shaping role early childhood has for human capital formation, growth and inequality. This is done in a synthetic, controlled world. Even though we tried to adjust the model world in a way that it hopefully captures some aspects of human capital in Germany, we only regard our approach as a first illustration. In future research, improved longitudinal and cross-section data, both experimental and non-experimental, could be collected in order to upgrade the empirical understanding of the cumulative and synergetic nature of skill formation and the way families, schools, and policies shape the future workforce.

A simulation model is presented which allows an illustration of three reasons underlying the heterogeneity of skill development and its long run consequences for human capital formation over the life cycle. First, the learning multiplier decreases with age. The learning multiplier for cognitive skills is higher than for self-regulatory skills until the age of twelve. Afterwards investments in self-regulatory skills will be more effective. The second type of heterogeneity of skills stems from differential investments in skills or socio-economic environments. In this variant, all individuals are the same, but differ only with regard to the inputs they receive from their environment. The third type of heterogeneity results from individual differences in the ability to transform an educational investment into additional skills. In that case, individuals all receive the same investment, but differ in the ability to transform investments into skills.

We compare absolute and relative rates of returns to an additional investment impulse during early childhood and in primary, secondary, and tertiary education for a population of seven heterogenous individuals. The rates of returns are assessed for full time dependent workers in Germany over the period from 18 to 65. If our synthetic society wants to maximize the sum of the additional human capital formed by limited additional resources for investments in education, the best strategy is to invest in early childhood. Due to the cumulative nature, returns are the higher the earlier an investment takes place. Furthermore, society should invest scarce resources in students from a bright environment or with bright learning abilities. If instead the goal of the society is the maximization of the relative returns to each individual, limited resources for additional educational investments should also be directed to early childhood, but they should be provided to the most disadvantaged if heterogeneity results from the environment. On the other hand, if heterogeneity stems from individual giftedness, investments should be directed to the most gifted individuals. Differences in individual giftedness thus have a higher impact on inequality than differences stemming from the environment. This results from the basic properties of self-productivity in the technology of skill formation.

The findings may have implications for human capital investment strategies. If the source of heterogeneity stems from varying individual abilities to transform educational inputs into new additional skills instead of socio-economic heterogeneity of families, compensating policies directed, for instance, to equity goals need much more resources to be successful. A reasonable strategy for fostering human capital is to supply children with symmetric impulses into cognitive and self-regulatory skills until they reach early adolescence. In later adolescence, however, investments in self-regulatory skills are more profitable. The incentives to attend education are highest in countries where the labour market leads to a high wage inequality. High labour market inequality generally increases the returns to education.

Further analyses, not reported in detail here (see Pfeiffer and Reuß (2007)), indicate that if it is not possible, for whatever reasons, to invest in early childhood, an increase in life expectancy seems to enhance returns to tertiary education specifically for students from disadvantaged environments. The relative gains from tertiary instead of primary additional education seem to be the higher the longer life expectancy lasts.

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Figures

Figure 1: Learning multipliers from age 0 to 50

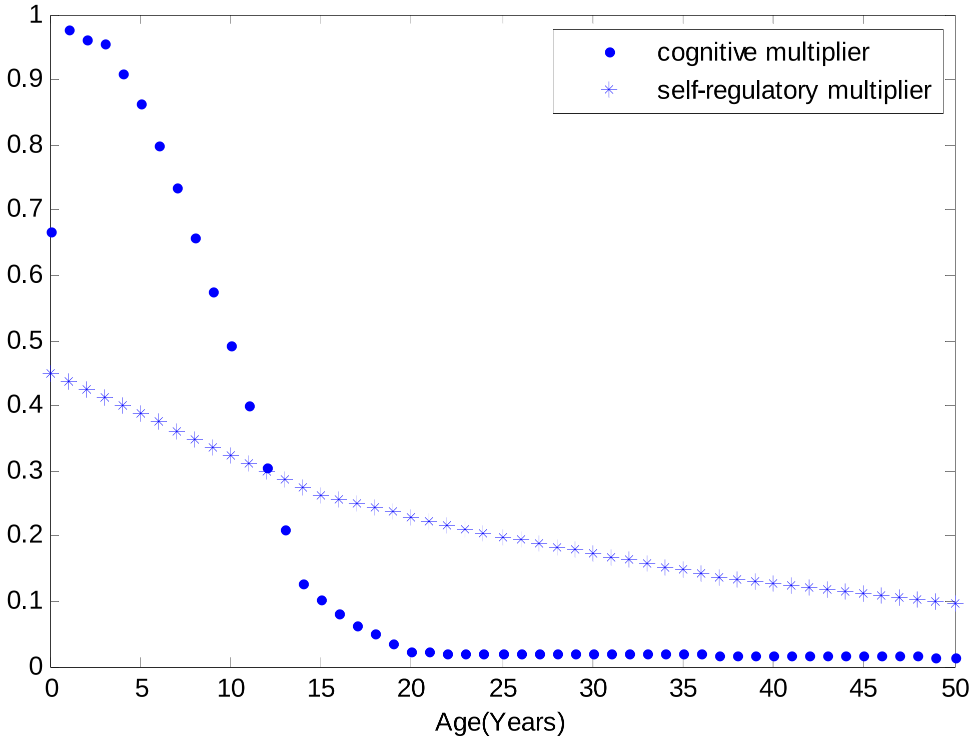


Figure 2: Skill development from age 0 to 80

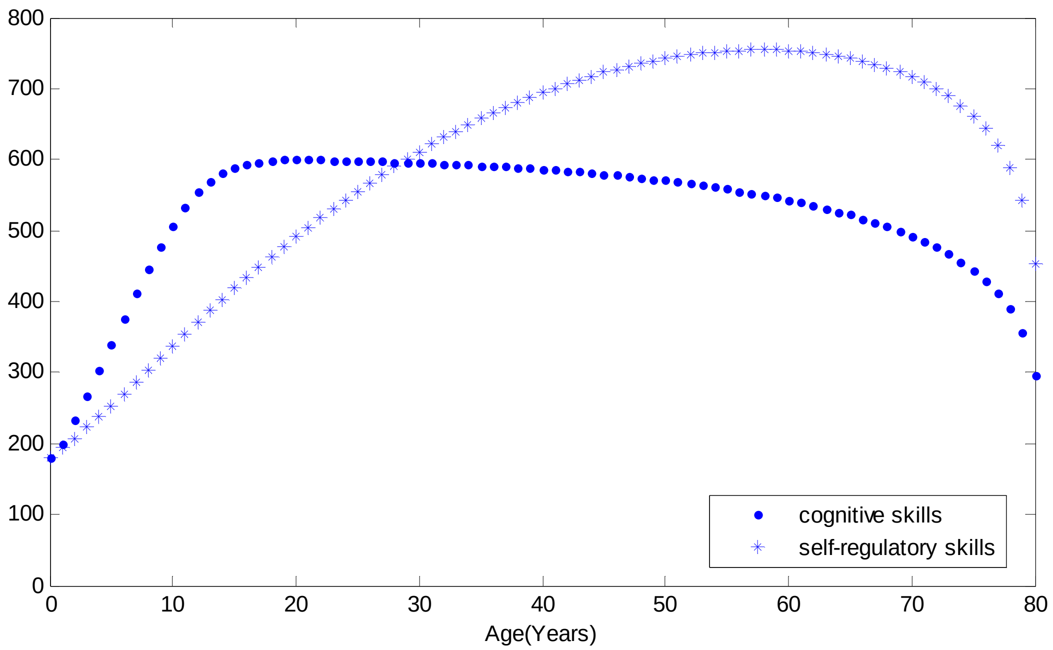


Figure 3: Achievement scores from age 0 to 80

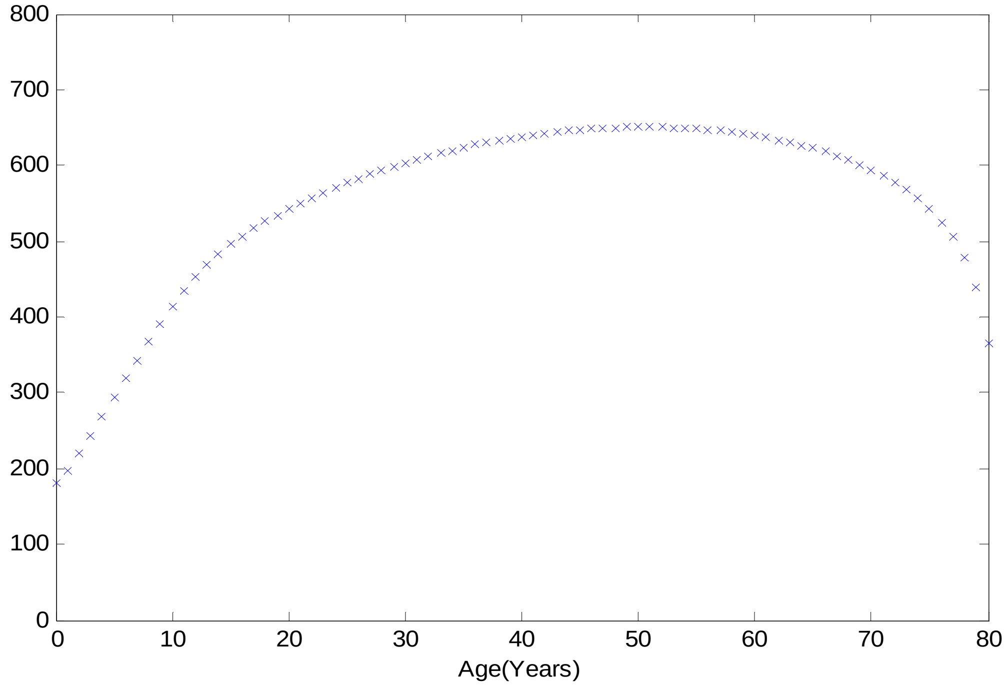


Figure 4: Annual human capital from age 0 to 80

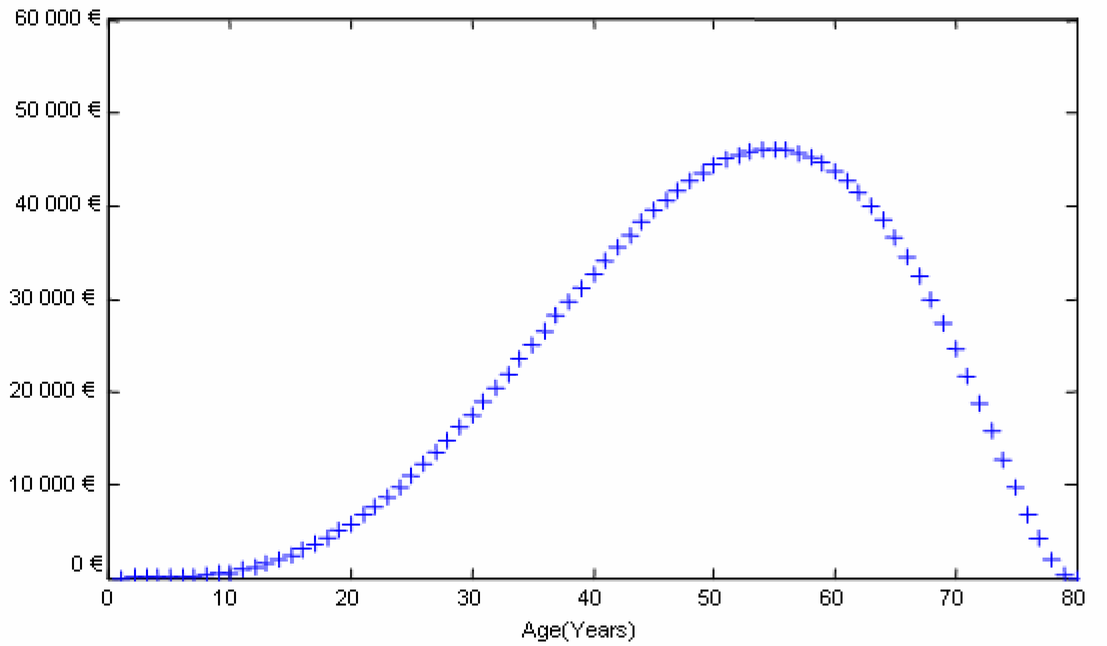
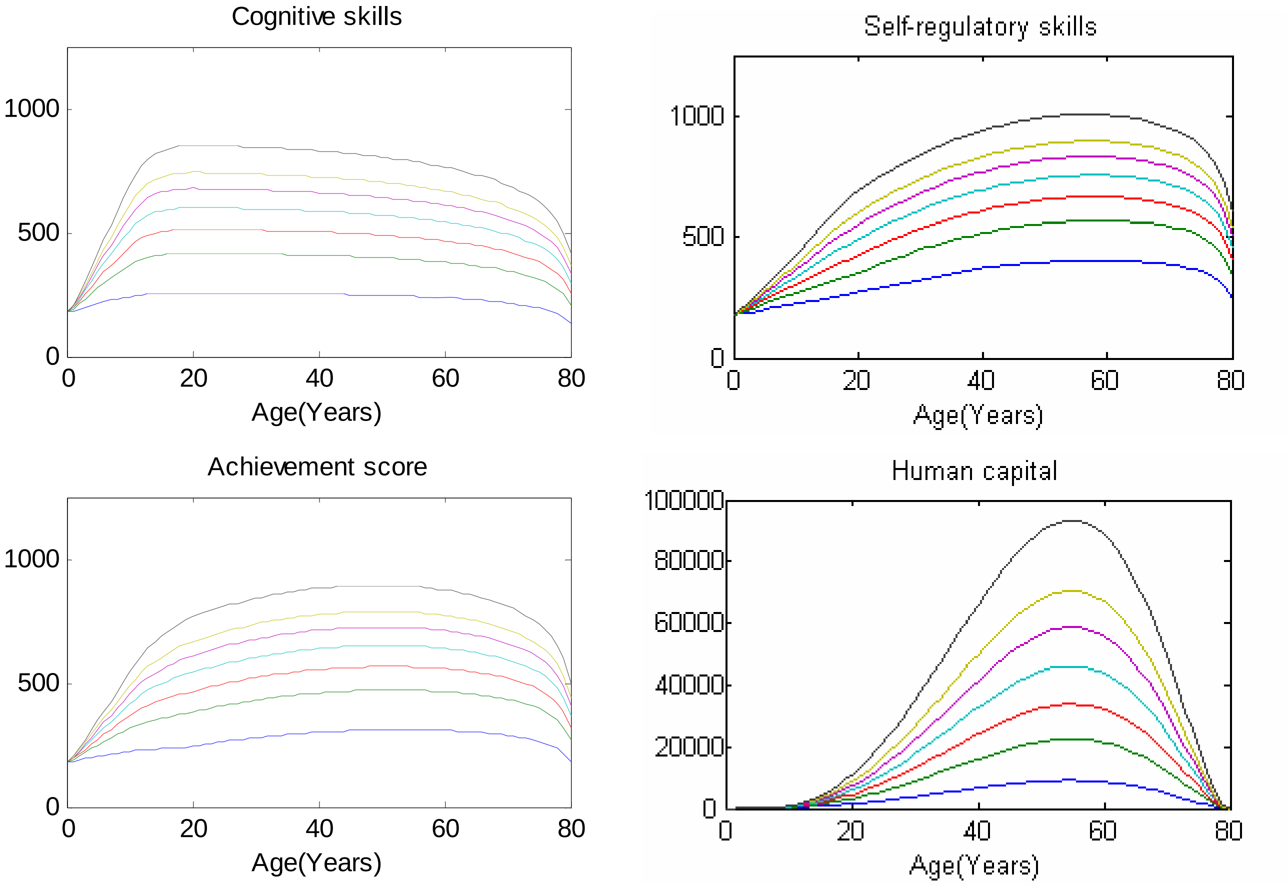


Figure 5: A population of seven individuals with heterogeneous environments



Tables

Table 1: 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: The PISA distribution for different types of heterogeneity

Percentile	Variation of $I_0^k ... I_{80}^k$	Variation of δ	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 3: 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 4: 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 5: Returns to education in Euros and relative returns for heterogeneous giftedness and environment, discounted to period 18

		Giftedness						
Environment	Percentiles	1.	10.	25.	50.	75.	90.	99.
	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 6: Utility maximizing duration of tertiary education in years

		Giftedness						
Environment	Percentiles	1.	10.	25.	50.	75.	90.	99.
	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 7: 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 8: 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%