Human Capital Production and Parental Beliefs

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In this paper we incorporate parental beliefs about returns to parental time investments in the estimation of a human capital production function. We proceed in three steps. First, we use data collect on parental beliefs about returns to parental time investments using hypothetical scenarios to predict parental investments. Second, using the British Cohort Study we estimate a dynamic latent factor model of cognitive and noncognitive skill production and document how these skills map into outcomes over the lifecycle. Third, we combine the estimates from the two previous steps to simulate the effect of a shift in beliefs on investments and child outcomes. We find that increasing beliefs about the returns to investments for parents with low perceived returns has large payoffs in terms of the future earnings of a child. The gains from increasing beliefs are greatest for children with parents at the bottom of the income distribution.

Keywords: Human Capital, Beliefs, Inequality, Intergenerational Mobility, Cognitive Skills, Noncognitive Skills

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1. Introduction

In her very first speech as the UK's prime minister in July 2016, Theresa May vowed to fight "burning" inequalities. One of her first actions was to launch an audit in order to "highlight the differences in outcomes for people of different backgrounds, in every area from health to education, childcare to welfare, employment, skills and criminal justice" while adding that "only by doing so we can make this country work for everyone, not just a privileged few".[1] Given the comparably high levels of income inequality and intergenerational earnings persistence, these quotes might not come as a surprise. However, the fact that they are voiced by the leader of the Conservative Party, a traditionally center-right party, reveals the level of concern skill disparities and the lack of intergenerational mobility have triggered in the UK. Blanden, Gregg and Macmillan (2007) document that in the UK intergenerational income persistence is high and that there are large socio-economic differences in children's cognitive and noncognitive skills that contribute to the intergenerational persistence in income.[2] This draws attention to the role of the family environment in the skill formation process.

Recent research has emphasized the importance of parental inputs for skill formation (e.g., Cunha, Heckman and Schennach 2010; Attanasio et al. 2013; Gayle, Golan and Soytas 2015; Agostinelli and Wiswall 2016*a*). Moreover, it has been well documented that the amount of time parents spend with their children engaging in educational activities varies considerably across families and tends to be significantly lower in socio-economically disadvantaged families.[3] This raises the important question of why we observe these large differences in parental investments across the population. Is the large and systematic variation in parental investments driven by differences in parental beliefs about the returns to parental investments? And if this is so, do we find evidence that the productivity of parental investments is indeed different across socio-economic groups? We know little about what parents believe about the impacts of their investments and even less about the effects differences in parental

[1] See press release from 27th of Aug 2016 on www.gov.uk/government/news.

[2] See Black and Devereux (2011) or Guner (2015) for recent overviews on intergenerational mobility.

[3] See Carneiro, Heckman and Masterov (2005); Todd and Wolpin (2007); Guryan, Hurst and Kearney (2008); Ramey and Ramey (2010); Lareau (2011); Carneiro, Meghir and Parey (2013); Attanasio et al. (2013); Gayle, Golan and Soytas (2014); Deckers et al. (2015); Gayle, Golan and Soytas (2015); Putnam (2015).

beliefs have on adult outcomes. Skills are multi-dimensional and the returns to investments depend on their timing. Given the complexity of the human capital production process it seems important to document how parents perceive the technology of skill formation and to understand what role parental beliefs play.

In order to shed light on these questions we proceed in three steps. First, we collect survey data which informs us about how beliefs about returns to parental time investments map into parental investments. Second, using data from the British Cohort Study (BCS) we estimate a dynamic latent factor model of cognitive and noncognitive skill formation using a newly developed approach by Agostinelli and Wiswall (2016*a*). This step informs us about how investments map into skills and how skills map into adult outcomes over the lifecycle. Moreover, we can compare perceived returns from step one to our estimates of the real returns from step two. Now that we know how beliefs map into investments, investments map into skills, and how skills map into adult outcomes, as a third step we can conduct counterfactual simulations. We simulate a shift in *parental* beliefs, which could be interpreted as a belief treatment along the lines of Alan, Boneva and Ertac (2015). They design an intervention in which they convey the idea of malleability of skills and the importance of grit to *children* finding considerable effects on both effort and outcomes.

The BCS is a particularly useful panel study as it follows a cohort born in 1970 throughout adulthood and provides detailed information on parent and child characteristics and investments at multiple stages of childhood. However, the BCS does not contain any information on parental beliefs about returns to investments. To elicit parental beliefs about how parental investments map into their children's future earnings, we survey 1,700 parents of primary and secondary school children in the UK. In addition to eliciting beliefs, we collect detailed information on parental investment activities and parent and child characteristics. To elicit parental beliefs about the productivity of investments, we build on the approach developed by Cunha, Elo and Culhane (2013), who make an important contribution to the literature by developing a method to elicit parental beliefs about the returns to investments using hypothetical investment scenarios.[4] In our survey we construct scenarios by replicating the types

[4] Zafar (2011) shows that elicited beliefs can be used to inform educational choice models.

of parental investments included in the BCS. Information on parental investments is collected as part of the BCS when children are 5 and 10 years old and the investments are age-specific (e.g., reading to child at age 5, talking to child about school at age 10). By using the same measures of investments in our survey as in the BCS, we can quantify how beliefs contribute to the dispersion of skills and adult outcomes.

The contribution of this paper can be summarized in terms of three main findings. First, we document that there is a significant amount of heterogeneity in parental beliefs which accounts for 2% of the overall heterogeneity in discounted lifetime income and 6% of the intergenerational earnings persistence. Our simulations suggest that interventions targeting low beliefs are likely to have large payoffs. Shifting beliefs about returns to investments for all parents with below 'true' beliefs leads to a mean increase of about £8,000 per capita in terms of discounted lifetime earnings for children of treated parents. This corresponds to an average effect of £4,000 per capita for the entire sample and 1.7% of total income earned between ages 26-42. Gains from shifting beliefs are greatest for children with poor parents. Second, we document socio-economic differences in perceived returns. In particular, parents with low household income are more likely to perceive the returns to parental time investments to be lower.[5] At the same time, we find that estimated returns to parental time investments are independent of current skill levels or parental characteristics; i.e. our evidence suggests that parents from different socio-economic groups are equipped with the same production technology but differ in terms of their beliefs about it. Third, we document that parents, on average, highly overestimate returns to late investments. Though we find returns to late investments to be high, parents believe they are nearly double of our estimate.

Our results suggest that parental investments and child development in disadvantaged families are constrained by beliefs. While traditional models of parental investments have pointed out the importance of credit constraints for differences in investments across socio-economic groups (Restuccia and Urrutia 2004; Caucutt and Lochner 2012; Lee and Seshadri 2014), the

[5]In Boneva and Rauh (2016), we use the same data in combination with an additional survey we conducted to document in detail how parents perceive the dynamic properties of the skill production function. We find that patterns of responses are extremely consistent across the two independent surveys.

findings in this paper suggest that socio-economic differences in investments might also be driven by socio-economic differences in parental beliefs about the returns to investments.

Our study contributes to several strands of existing literature. First, we build on and contribute to the literature that estimates the human capital production function. The seminal work by Cunha, Heckman and Schennach (2010) considers the dynamic nature of the skill accumulation process and the multi-dimensionality of skills while at the same time dealing with the fact that measurements of skills suffer from measurement error. The findings of this paper sparked a larger literature of empirical work which investigates the optimal timing of investments and the dynamic properties of the skill production function (e.g., Del Boca, Flinn and Wiswall 2014; Heckman and Kautz 2014; Attanasio, Meghir and Nix 2015; Attanasio et al. 2015). A new approach by Agostinelli and Wiswall (2016*a*,*b*) provides a tractable estimation technique which we employ in this paper. We contribute to this literature by investigating how parental beliefs map into parental investments, how parental investments in different periods of childhood map into cognitive and noncognitive skills, and how these skills map into adult outcomes at different points in the lifecycle.

Concerning the timing of investments, we investigate how parents perceive the relative productivity across different periods of childhood, as this will have implications on their allocation of investments across time periods. On the one hand, empirical evidence suggests that skills acquired at earlier ages increase the productivity of later investments because of important dynamic complementarities in the skill accumulation process ('skills beget skills') (e.g., Heckman 2006; Cunha, Heckman and Schennach 2010; Caucutt and Lochner 2012; Heckman and Mosso 2014; Attanasio et al. 2015). On the other hand, Attanasio, Meghir and Nix (2015) and Carneiro et al. (2015) investigate the impact of parental investments and resources at multiple stages of childhood, finding that shifting resources from middle periods of childhood to adolescence might indeed be optimal. We find evidence in favor of the latter.

Second, we contribute to the literature which investigates the role of beliefs in educational investment decisions. The literature on parental investments in children, pioneered by Becker and Tomes (1979, 1986), traditionally assumes that parents are perfectly aware of the exact characteristics of the human capital production function. Recent studies relax this assumption and emphasize the importance of parental beliefs in the skill accumulation process.[6] Caucutt, Lochner and Park (2015) develop a theoretical framework to explore whether parental beliefs can explain inefficiently low investments observed in the data. Dizon-Ross (2014) finds that parents in Malawi allocate educational investments according to their (inaccurate) beliefs about their children's academic achievements and reoptimize in light of an information treatment.[7] Our study also relates to the growing literature documenting the importance of individual beliefs about returns to schooling in students' schooling decisions. Attanasio and Kaufmann (2009, 2014) and Kaufmann (2014) document students' and parents' beliefs about the returns to formal education and the effects on students' decisions to spend more time in education. Jensen (2010) shows that students' perceived returns to schooling can differ from returns observed in the data, and that an intervention which informs students about returns increases school attendance.[8] Our study most closely relates to Cunha (2014), who investigates the role of parental beliefs in explaining differences in parental investments using the data from Cunha, Elo and Culhane (2013). He finds that equalizing beliefs across black and white mothers in the US would increase the black-white ratio in terms of investments in children aged 0-2 from 78% to 84%. In our approach we look at multiple periods of a child's school life and are able to gain an understanding of how parental beliefs during childhood affect multiple adult outcomes, e.g. earnings, employment, or marriage, over the lifecycle.

This paper proceeds as follows: Section 2 presents the model of parental investments and the human capital production technology. Section 3 presents the BCS and the survey data, whereas Section 4 describes the survey design we use to elicit parental beliefs. Section 5 presents the main results, while Section 6 presents the outcomes of our counterfactual simulations. Section 7 provides a discussion of the main findings, while Section 8 concludes.

[6] In his EEA presidential address, Attanasio (2015) stresses the importance of investigating the role of parental beliefs in understanding parental investment decisions and child outcomes.

[7] Similarly, Kinsler and Pavan (2016) explore the possibility that parents in the US misallocate investments due to inaccurate beliefs about the relative performance of their child.

[8] Our work also relates to the literature which investigates the role of students' beliefs in explaining choices of high school tracks, college majors, and university attendance (Dominitz and Manski 1996; Montmarquette, Cannings and Mahseredjian 2002; Arcidiacono 2004; Arcidiacono, Hotz and Kang 2012; Beffy, Fougere and Maurel 2012; Zafar 2013; Arcidiacono et al. 2014; Stinebrickner and Stinebrickner 2014; Delavande and Zafar 2014; Wiswall and Zafar 2015; Belfield et al. 2016; Giustinelli and Pavoni 2016; Giustinelli 2016).

2. Model

Child development takes place over several discrete periods of time, $t = \{0, ..., T\}$, where $t = 0$ is the initial period and $t = T$ is the final period of childhood. In the following, we first specify the skill production function that maps skills and investments in t into skills in $t+1$. Second, we specify the investment function which maps parent and child characteristics as well as parental beliefs into parental investments. Third, we set out the initial conditions. Fourth, we specify how skills at the end of childhood map into adult outcomes. Finally, we describe the system of measurements.

2.1. Skill Production Technology

In each period $t < T$, every child i is endowed with a two-dimensional vector of skills, $\theta_{i,t}$, where the two dimensions are the child's cognitive skills, $\theta^C_{i,t}$, and noncognitive skills, $\theta^{NC}_{i,t}$. Skills in period $t+1$ are a function of skills in the previous period, $\theta_{i,t}$, and investments made in the previous period, $I_{i,t}$. For simplicity we drop subscript i in what follows. As in Agostinelli and Wiswall (2016a), we assume that the production technology takes a stochastic specification, which is linear in logs. In particular, we model the level of cognitive skills in period $t+1$ as:

$$\ln \theta^C_{t+1} = \gamma^C_{1,t} \ln \theta^C_t + \gamma^C_{2,t} \ln \theta^{NC}_t + \gamma^C_{3,t} \ln I_t + \eta_{C,t} \tag{1}$$

where $\sum_{j=1}^{3} \gamma^C_{j,t} = 1$ and $\eta_{C,t}$ is the stochastic production shock to cognitive skills, which is assumed to be $i.i.d. \sim N(0, \sigma^2_{C,t})$. Similarly, we model the level of noncognitive skills in period $t+1$ as:

$$\ln \theta^{NC}_{t+1} = \gamma^{NC}_{1,t} \ln \theta^C_t + \gamma^{NC}_{2,t} \ln \theta^{NC}_t + \gamma^{NC}_{3,t} \ln I_t + \eta_{NC,t} \tag{2}$$

where $\sum_{j=1}^{3} \gamma^{NC}_{j,t} = 1$ and $\eta_{NC,t}$ is the stochastic production shock to noncognitive skills, which is assumed to be $i.i.d. \sim N(0, \sigma^2_{NC,t})$. We assume that $\eta_{C,t}$ and $\eta_{NC,t}$ are independent of the current stock of skills and investment.

There are several features of this technology which are worth noting. First, the parameters of the skill production function are indexed with t, indicating that the characteristics of the production function are allowed to vary with each period of childhood. This flexible formulation allows the returns to investments to differ across different periods of childhood, which is important given that there might be 'critical' periods during which investments in children are particularly productive.

Second, the production technology is in the class of production technologies that have a *known location and scale (KLS)*, in the sense that it does not depend on any unknown (free) parameters that have to be estimated (Agostinelli and Wiswall 2016*a*,*b*). This feature is important for the identification of the model, which we discuss in detail in Appendix A.

2.2. Parental Investments

We model parental investments as a function of child and parent characteristics as well as parental beliefs. Motivated by the finding of Cunha, Elo and Culhane (2013) that boys receive less investments than girls, we consider gender as well. More specifically, investments in t, I_t, are a function of the child's cognitive and noncognitive skills in t, θ_t^C and θ_t^{NC}, parents' cognitive and noncognitive skills that are assumed to be fixed over time, P^C and P^{NC}, whether the child is a male, M, and parental beliefs about the returns to investments in period t, ϕ_t:

$$\ln I_t = \alpha_{1,t} \ln \theta_t^C + \alpha_{2,t} \ln \theta_t^{NC} + \alpha_{3,t} \ln P^C + \alpha_{4,t} \ln P^{NC} + \alpha_{5,t} M + \alpha_{6,t} \phi_t + \eta_{I,t} \tag{3}$$

where $\sum_{j=1}^{6} \alpha_{j,t} = 1$ and $\eta_{I,t}$ is the shock to parental investments, which is assumed to be *i.i.d.* $\sim N(0, \sigma_{I,t}^2)$ and independent of skills and beliefs about the returns to investments.

The parameters $\alpha_{1,t}$ and $\alpha_{2,t}$ reflect whether parents compensate or reinforce existing skill levels. The extent to which parental investments are related to parental cognitive and noncognitive skills is captured by $\alpha_{3,t}$ and $\alpha_{4,t}$. The investments male children receive beyond what female children with the same characteristics receive is given by $\alpha_{5,t}$. Most importantly, the parameter $\alpha_{6,t}$ reflects the degree to which parental investment decisions are related to parental beliefs about the returns to investments in period t.

We follow the approach in the literature (Cunha, Elo and Culhane 2013; Attanasio et al. 2015; Attanasio, Meghir and Nix 2015; Agostinelli and Wiswall 2016*a*) and estimate a 're-duced form' specification which represents a policy function for parental investment that is not derived from a model of parental decision-making. An advantage is that it simplifies estimation substantially and has a straightforward interpretation. Given that we do not model the time constraint of parents explicitly, this approach comes at the cost of not being able to perform welfare analyses in which we would have to account for parental changes in hours worked or leisure when we simulate changes in investments.

2.3. *Initial Conditions*

The vector of initial conditions consists of the child's cognitive and noncognitive skills at $t = 0$, the parent's cognitive and noncognitive skills, which are assumed to be fixed over time, and parental beliefs about the returns to investments:

$$\Omega = (\ln \theta_0^C, \ln \theta_0^{NC}, \ln P^C, \ln P^{NC}, \phi) \tag{4}$$

where $\phi = (\phi_0, ..., \phi_{T-1})$ is a vector of beliefs about returns to parental investments made during the different periods of childhood. We assume a parametric distribution for the initial conditions:

$$\Omega \sim N(\mu_\Omega, \Sigma_\Omega) \tag{5}$$

where μ_Ω is the mean vector and Σ_Ω is the variance-covariance matrix.

2.4. *Adult Outcomes*

Finally, we are interested in how skills in the last childhood period T map into outcomes later in life. Adult outcomes Q are realized in periods $T + l$ where $l \in \{1, ..., L\}$ and are a function of cognitive and noncognitive skills in the final period of childhood, θ_T^C and θ_T^{NC}, as well as gender, M:

$$Q_{T+l} = \mu_{Q,l} + \alpha_{1Q,l} \ln \theta_T^C + \alpha_{2Q,l} \ln \theta_T^{NC} + \alpha_{3Q,l} M + \eta_{Q,l}. \tag{6}$$

2.5. Measurement System

The empirical challenge in estimating the skill formation process is that skills and investments are not directly observed. Instead we have multiple measures of skills and investments. Each of these measures is likely to be imperfect, i.e. measured with error, to have an arbitrary location and scale, and to provide a different level of informativeness about the underlying latent factor. For each latent factor ω, each measure takes the following form:

$$Z_{\omega,t,m} = \mu_{\omega,t,m} + \lambda_{\omega,t,m} \ln \omega_t + \epsilon_{\omega,t,m},$$

where $Z_{\omega,t,m}$ are the measures (indexed by m for each latent factor $\omega \in \{\theta^C, \theta^{NC}, I, P^C, P^{NC}\}$), $\mu_{\omega,t,m}$ are the measurement intercepts, and $\lambda_{\omega,t,m}$ are the factor loadings, which are assumed to be non-negative, and $E[\epsilon_{\omega,t,m}] = 0$.

Given that latent skills and investments do not have a natural location and scale, some normalization is required to fix the location and scale of the latent skills and investments. In particular, we follow Agostinelli and Wiswall (2016*a*) and normalize each latent factor to one of the measures of the initial period, where the choice of the measure $m = 1$ is arbitrary:

1) $E[\ln \omega_0] = 0 \ \forall \omega$

2) $\lambda_{\omega,0,1} = 1 \ \forall \omega$.

Note that each latent factor shares the same scale of the respective normalizing measure. Therefore, a one-unit increase in the log latent factor ω is equivalent to a one-unit increase in the level of the normalized measure $Z_{\omega,0,1}$. By normalizing for the initial period only, latent skills in all periods share a common location and scale with respect to the chosen normalizing measure.

There are several advantages to using the specified measurement system. First, the free measurement parameters $\mu_{\omega,t,m}$ and $\lambda_{\omega,t,m}$ for each measure allow the measurement model to capture the arbitrary location and scaling of the different measures. Put differently, the estimates of the production function will be robust to changes in the location and scale of the measures (up to the initial normalization). Second, the system allows for measurement error and for measures to differ in their noise-to-signal ratio, thus allowing some measures to have higher correlations to the latent factors than others.

2.6. *Empirical Specification*

In the empirical specification we estimate, we have three periods of child development which correspond to age 5 ($t = 0$), age 10 ($t = 1$) and age 16 ($t = T = 2$). We hence estimate the skill production functions for cognitive and noncognitive skills at age 10 as a function of inputs at age 5, as well as the skill production functions for cognitive and noncognitive skills at age 16 as a function of inputs at age 10. Moreover, we estimate the investment functions at age 5 as well as at age 10. In addition to using the rich information in the BCS data, which we describe in detail in the following section, we also elicit parental beliefs about the returns to investments made during the different periods of childhood. In particular, we elicit parental beliefs about the returns to parental investments made at age 5 and at age 10, which allows us to estimate the parental investment functions. Adult outcomes, which are assumed to be a function of skills at age 16, are measured at ages 21, 26, 30, 34, 38, and 42. This allows us to obtain a detailed understanding of how skills measured at the end of high school map into adult outcomes at different points of the lifecycle. Finally, we assume assume that children's skills are measured with error, as are investments, and parents' cognitive and noncognitive skills.

3. Data

We use two sources of data. First, we use the British Cohort Study (BCS), which is a panel following all individuals born in one particular week in April 1970 in the UK. The BCS contains rich measures on child skills at age 5, age 10 and age 16, parent characteristics, as well as the investments that parents make at age 5 and age 10. However, it does not contain data on parental beliefs about the returns to parental investments. In order to estimate the investment functions, we therefore collect unique survey data which elicits parental beliefs about the returns to investments made at age 5 and age 10, and collects information on the levels of parental investments and child and parent characteristics. For our purposes it is crucial that we can combine information from the two sources. In the survey we conduct, we therefore replicate the investment questions which are administered as part of the BCS. This allows us to first estimate how parental beliefs map into parental investments using our survey data and to then estimate how parental investments map into skills and adult outcomes using the BCS data. As a third step, we can conduct simulations to assess the quantitative importance of parental beliefs. In addition, we can compare the beliefs of parents which we elicit in our survey to the estimates of returns to investments which we obtain from the BCS.

3.1. The British Cohort Study Data

The BCS is a panel study that follows about 17,000 individuals born in a specific week in 1970. To estimate the skill production function, we use individuals for whom the relevant information on child skills, parent characteristics and parental investments is available, which results in samples ranging from 1,243 and 4,237 individuals.[9] We use information on fours sets of different variables: (i) information on parents' cognitive and noncognitive skills, which we treat as fixed across periods, (ii) information on parental investments made at age 5 and at age 10, (iii) measures of children's cognitive as well as noncognitive skills at ages 5, 10, and 16, and (iv) adult outcomes measured at ages 21, 26, 30, 34, 38, and 42. We discuss each of these different sets of variables in turn. An overview of the measurements we use for the different latent factors is provided in Table 1.[10]

Parents' cognitive and noncognitive skills: As proxies for parental cognitive skills we use maternal education, paternal education, and whether the mother has problems reading. Con-

[9] We chose to estimate each specification with all available observations in order to reduce measurement error instead of limiting the sample to the relatively small number of individuals for whom we have information for every measure across all periods.

[10] A range of skills and investments, which are marked with a (-), are reversely coded and are therefore multiplied by -1 in the estimation, such that all coefficients have the same positive interpretation.

Table 1—: Overview of measures from BCS

Parents:		
Cognitive skills		Noncognitive skills
Maternal education		Malaise score(-)
Paternal education		Locus of control
Mother problems reading		Teacher evaluation(-)
	Investments	
Age 5		**Age 10**
Days read to per week		Joint family activities
Hours of TV(-)		Time talking to parents
Visit to park		Mother's interest in education
Children:		
	Cognitive skills	
Age 5	**Age 10**	**Age 16**
Copy score	Math score	Math score
EPTV	Reading score	Vocabulary score
Reading score	British Ability Scale	Spelling score
	Noncognitive skills	
Age 5	**Age 10**	**Age 16**
Rutter score(-)	Rutter score(-)	Rutter score(-)
Disobedience(-)	Locus of control	Locus of control
Restlessness(-)	Worriedness(-)	Self-confidence

Datasource: BCS.
Notes: EPTV stands for English Picture Vocabulary Test. Measures marked by (-) are assumed to be skills or investments that are not favourable.

cerning parental noncognitive skills, we use the mother's elicited Malaise score, locus of control, and an evaluation of whether the mother is dismissive or hostile as reported by the teacher of the child.[11]

Parental investments: We have three measurements for parental time investments at age 5. In particular, parents are asked to provide information on how many days their child has

[11]The Malaise score is computed as the sum of 22 questions pertaining to the mother's state of health and mind. The locus of control questionnaire is based on Gammage (1975) and captures the extent to which the mother feels in charge of her destiny. Example questions for both are presented in Appendix Table C1.

been read to at home in the past 7 days, how many hours per day the child usually watches TV, and whether the child has been taken to a park or playground during the past 7 days. We also have three measurements for parental time investments at age 10. In particular, we have parents' reports of the frequency of different activities that the parents do together with their child, teachers' reports of how interested the parents are in the child's education, as well as child's reports on how much time parents usually spend talking to their child every day.

We summarize the different measures of investments at age 5 by maternal education in Table 2. We see that the frequency of reading to a child and the probability of having visited a park with the child in the last week are generally increasing in maternal qualifications. The average mother with no qualification reads less than four times per week to her child, whereas mothers with a university degree read to their child on more than six days per week. While only about one-third of mothers with no qualification go to the park with their child, more than half of mothers with a university degree do so. The hours a child spends watching television per week, which we see as a negative investment, reduces from an average of nearly 12 hours for mothers with no qualification to nearly 6 hours for mothers with a university degree. Similar patterns can be found when we investigate parental investments by maternal education at age 10 (see Table 3).

Table 2—: Summary of investments at age 5 by maternal qualification

	Read	[SD]	TV	[SD]	Park	[SD]	Sample share
No qualification	3.71	[2.63]	11.76	[9.47]	.32	[.47]	.58
Vocational qualification	4.62	[2.46]	8.88	[7.87]	.4	[.49]	.14
O level	5	[2.33]	8.19	[7.56]	.41	[.49]	.17
A level	5.43	[2.15]	7.7	[7.4]	.5	[.5]	.04
SRN	5.45	[2.15]	7.61	[7.02]	.43	[.5]	.03
Certificate of education	6.28	[1.43]	6.17	[6.12]	.48	[.5]	.02
University degree	6.11	[1.66]	6.03	[6.59]	.53	[.5]	.03
Full sample	4.29	[2.59]	10.21	[8.9]	.37	[.48]	13,054

Datasource: BCS.
Notes: "Read" refers to the number of days a mother reads to a child per week, "TV" to the number of hours a child watches TV per week, and "Park" is a dummy capturing whether the child visited a park with an adult the past week.

Table 3—: Family activities at age 10 by maternal qualification

Maternal qualification	Less than O levels		At least O levels		Full sample	
Activity	Rarely	Often	Rarely	Often	Rarely	Often
Walks	.18	.23	.12	.28	.16	.25
Outings	.05	.51	.02	.57	.04	.53
Meals	.02	.88	.01	.91	.02	.89
Holidays	.11	.71	.05	.8	.09	.75
Shopping	.06	.57	.06	.54	.06	.56
Chat +5min	.01	.86	0	.91	.01	.88
Restaurant	.35	.15	.24	.17	.32	.15
Observations	9,457		3,880		13,015	

Datasource: BCS.
Notes: The omitted frequency category is "sometimes".

Children's cognitive and noncognitive skills: As measures for a child's cognitive skills we use scores of tests relating to (i) copying designs through drawings, the English Picture Vocabulary Test, and reading at age 5, (ii) maths, reading, and the British Ability Scale (similar to an IQ test) at age 10, (iii) and maths, vocabulary, and spelling at age 16.[12] As measures for a child's noncognitive skills we use (i) the Rutter scale, whether the child is disobedient, and whether the child is restless at age 5, (ii) the Rutter scale, locus of control, and a teacher evaluation provided on a sliding scale from 0 to 100 of whether the child is anxious at age 10, (iii) and the Rutter scale, locus of control, and the child's self-assessed level of self-confidence at age 16.[13]

Adult outcomes: Finally we look at how these skills map into a wide range of adult outcomes over the lifecycle, namely: educational attainment, earnings, hourly earnings, employment, unemployment, hours worked, marriage, smoking daily, arrest, detention, and self-reported life satisfaction. The follow-up surveys were conducted at ages 21, 26, 30, 34, 38, and 42.

[12]See Appendix C1 for descriptions and examples of cognitive tests.
[13]See Appendix Table C2 for a sample of questions.

3.2. The Parental Survey Data

The parental survey data we collect contain detailed information on parental beliefs, parental investments, and child, parent and household characteristics.[14] We collect the data using an online survey. The survey was distributed in May-June 2016 via the parental mailing list of 11 primary schools and 24 secondary schools in the UK that agreed to participate in the study (see map in Appendix B).[15] In total, we have complete responses from 1,705 parents.

Table 4 presents the descriptive statistics of the sample. 68% of the parents in our sample are female, 13% report being single parents, 82% report being employed, of which 69% are full-time employed, and 31% are employed part-time. 61% of the responding parents hold a university degree, and the average annual household income of the families in the sample is £78,992. The average number of children in the household is 2.28 of which 32% are female.

Table 4—: Descriptive Statistics

	Mean	[SD]
Female respondent	.68	[.47]
Employed	.82	[.39]
Part-time	.31	[.46]
Full-time	.69	[.46]
University graduate	.61	[.49]
Single parent	.13	[.34]
Number of children	2.28	[.94]
Age of child	13.03	[3.3]
Female child	.32	[.47]
Household income	78,992	[37,544]
Observations	1,705	

Datasource: Own survey.
Note: Household income refers to the gross annual income of all household members.

We use the Family Resources Survey, which is a representative survey of households in the UK, to compare the characteristics of our sample to a representative sample of parents

[14]See Boneva and Rauh (2016) for a more detailed description and analysis of the data collected.
[15]Participation in the survey was incentivized through a prize draw of a voucher worth £100.

in England with at least one child aged 5-19 years. While on average the parents in our sample are more educated and have higher income than a nationally representative sample, our sample of parents spans the entire distribution of income and education.

Parents are asked to provide information on the characteristics of one of their children (henceforth referred to as the *target* child).[16] To investigate the relationship between parental beliefs and investments, parents are also asked to provide information on their own parental investment activities.[17] We replicate the questions from the BCS and ask about the same age-specific investments, which we vary using hypothetical investment scenarios. In particular, we ask parents of children aged 3-9 to provide information on (i) how many days their child has been read to at home in the past 7 days, (ii) how many hours per day the child usually watches TV, and (iii) whether the child has been taken to a park or playground during the past 7 days. Parents of children aged 10 or above are asked about (i) the frequency of different activities they do together with their child (e.g., have breakfast or tea together), (ii) how interested they are in their child's education, and (iii) how much time they usually spend talking to their child every day.[18] Tables 5 and 6 present the summary statistics of the responses to these different questions.

Table 5—: Time investments (age 5)

	Mean	[SD]	Min	Max	Median
Visits park with child in a given week	.86	[.35]	0	1	1
Hours of TV child watches per day	1.47	[1.03]	0	7	1
Days parent reads to child per week	5.17	[2.04]	0	7	6

Datasource: Own survey.

[16]The questionnaire instructed parents to fill out the survey for the child who attended the school via which the survey was distributed. If the parent had more than one child attending this school, parents were asked to provide information on the youngest child only.

[17]Note that in the survey we randomized the order of the section which elicited parental beliefs and the section which asked parents to self-report their investments. Our analysis reveals that the patterns of the results are robust to controlling for potential order effects.

[18]Concerning parental investments at age 5, parents with children aged 3-7 were asked these questions prospectively, while those with children aged 8-9 were asked these questions retrospectively. Similarly, parents with children aged 10-12 were asked about their investments in children prospectively, while those with children aged 13 or above were asked about the investments they made into their children retrospectively.

Table 6—: Family activities (age 10)

	1	2	3	4	5
Go for walks together	.02	.11	.4	.33	.14
Have breakfast/tea together	0	.03	.1	.25	.61
Have a chat with the child	0	.01	.04	.22	.73
Interested in child's education	0	.01	.06	.45	.47
Time spent talking to child	0	.03	.3	.41	.26

Datasource: Own survey.
Notes: Parents were asked to give their responses on a 5-point Likert scale. For items 1-3, the Likert scale ranged from 'Never' (1) to 'Very often' (5). For item 4, the scale ranged from 'Not interested at all' (1) to 'Extremely interested' (5), while for item 5 the scale ranged from 'None at all' (1) to 'A great deal' (5). The numbers reported are the shares of parents that chose a specific answer.

Note that in order to estimate equation (3), we also require information on parental cognitive and noncognitive skills. An overview of the measures is provided in Table 7. For parental cognitive skills we use level of education of the respondent. Due to a lack of further proxies we assume that this is measured without error. We replicate a subset of the questions from the BCS in order to have comparable measures of noncognitive skills, which are summarized in Appendix Table E12.[19] As a measure for children's skills we use the parental evaluation of their child's skills on a scale from 0-100 concerning the child's school performance, and mathematical as well as verbal skills, which are summarized in Appendix Table E11. For a child's noncognitive skills, we use a subset of questions of the Rutter score as administered in the BCS. The questions and responses are summarized in Appendix Table E11.

4. Survey Methodology

In this section, we provide details on how we elicit parental beliefs about the returns to parental investments. In particular, we present parents with different hypothetical investment scenarios and ask them to report what they believe the likely outcome of each scenario to be. This survey methodology has been successfully used in the past. For example, Cunha, Elo

[19]To keep the survey sufficiently short we could only include a subset of questions.

Table 7—: Overview of measures from survey

Parents:	
Cognitive skills	Noncognitive skills
Maternal education	Easily irritated(-)
	Rushed(-)
	Depressed(-)
Investments	
Age 5	**Age 10**
Days read to per week	Joint family activities
Hours of TV(-)	Time talking to parents
Visit to park	Mother's interest in education
Children:	
Cognitive skills	
Age 5	**Age 10**
Math score	Math score
Verbal score	Verbal score
School performance	School performance
Noncognitive skills	
Age 5 and 10	
Restless(-)	
Miserable or unhappy(-)	
Disobedient(-)	

Datasource: Own survey.
Notes: Measures marked by (-) are assumed to be skills or investments that are unfavourable.

and Culhane (2013) survey a sample of socio-economically disadvantaged pregnant African-American women in the U.S. to elicit parental beliefs about the technology that maps parental investments in children aged 0-2 into children's skill levels. In Boneva and Rauh (2016) we find that parental responses are very consistent across two independent surveys.

In this survey, we elicit parental beliefs about the returns to investments that parents make at age 5 and at age 10.[20] We are specifically interested in how parents perceive the returns

[20]We chose to elicit parental beliefs about the returns to investments at age 5 and at age 10 because the BCS data contains information on parental investments at age 5 and at age 10. This allows us to combine information from the two data sources when we estimate the model.

to investments in period t on future outcome Q_{T+l}:

$$\phi_t = \frac{\partial Q_{T+l}}{\partial I_t}. \tag{7}$$

In particular, we look at parental beliefs about a child's earnings y at age 30. To elicit parental beliefs about this partial derivative, we present parents with different hypothetical investment scenarios that vary along three key dimensions: (i) the level of parental investments at age 5, (ii) the level of parental investments at age 10, and (iii) the initial human capital level of the child.[21] All parents are presented with two hypothetical families (the 'Jones' and the 'Smiths') with one 5-year-old child each. Parents are told that while the Jones and the Smiths live in the same neighbourhood and are similar in many different respects (e.g. in terms of income and education), their children differ in how intelligent they are. In particular, parents are told that on an intelligence test the child of the Jones scored better than 70% of all children in the same age group, while the child of the Smiths scored worse than 70%.[22] For each of these hypothetical families, parents are then presented with four different investment scenarios. Those investment scenarios differ in the level of parental investments at age 5 and at age 10. The four investment scenarios are (1) low age 5 investments/low age 10 investments, (2) low age 5 investments/high age 10 investments, (3) high age 5 investments/low age 10 investments and (4) high age 5 investments/high age 10 investments. In total, parents are hence presented with *eight* different scenarios, which are illustrated in Table 8. For each of these eight scenarios j, parents are asked to state what they expect the gross annual earnings of the child to be when the child is 30 years old (y_j).[23]

[21] The full questionnaire can be found in Appendix B.

[22] Note that the gender of the child in the scenario was chosen to match the gender of the target child, i.e. the child for whom the parent completed the survey. Parents who filled out the survey for their daughter were presented with 'Jessica Jones' and 'Sarah Smith' while parents who filled out the survey for their son were presented with 'John Jones' and 'Simon Smith'.

[23] Parents are instructed to assume that the child is working full-time at age 30 and they are asked to report their response in £ assuming no inflation. We ask parents about the earnings of the child at age 30 because by that time most individuals have completed their education and have entered the labor market. It seems likely that the perceived returns we document can be interpreted as a lower bound to the perceived return to parental investments on lifetime earnings since individuals with higher levels of earnings at age 30 are more likely to experience steeper earnings growth profiles over their lifecycle. Asking parents directly about the likely outcomes of these scenarios, and not about interim

Table 8—: Overview of Different Scenarios

A: The Jones
High Initial Human Capital

	Low Age 10 Investment	High Age 10 Investment
Low Age 5 Investment	y_1 Low age 5/ Low age 10	y_2 Low age 5/ High age 10
High Age 5 Investment	y_3 High age 5/ Low age 10	y_4 High age 5/ High age 10

B: The Smiths
Low Initial Human Capital

	Low Age 10 Investment	High Age 10 Investment
Low Age 5 Investment	y_5 Low age 5/ Low age 10	y_6 Low age 5/ High age 10
High Age 5 Investment	y_7 High age 5/ Low age 10	y_8 High age 5 / High age 10

The descriptions of the scenarios are chosen so that the types of investments described in the scenarios match the types of investments which parents are asked about in the BCS. This allows us to effectively combine information from the two data sources. When choosing the levels of *low* and *high* investments, we choose values which are ± 0.5 standard deviations from the mean response of parents in the BCS.[24] In scenarios in which age 5 investments are *low*, respondents are presented with a hypothetical scenario in which the parents read to their child every second day, rarely take their child to the playground, and let their child watch TV for 2 hours every day. In contrast, for scenarios in which the level of age 5 investments is *high*, parents read to their child every day, take their child to the playground once every fortnight, and let their child watch TV for 1 hour every day. In scenarios in which age 10 investments are *low*, parents show moderate interest in their child's education, don't talk to their child very much, and sometimes engage in activities together (e.g. go out for walks, have breakfast or tea together). In contrast, in scenarios in which age 10 investments are *high*, parents show a lot of interest in their child's education, talk to their child quite a lot, and often engage in

test scores, has the advantage that we can directly calculate expected returns without having to make assumptions about the returns of arbitrarily scaled test scores. Moreover, by presenting parents with hypothetical investment decisions of hypothetical families, we can hold a series of factors constant, such as household, child and neighbourhood characteristics.

[24]More specifically, we extract one factor each from the investments at age 5 and 10, and then look at responses of parents for whom the factor is ± 0.5 standard deviations from the mean.

activities together.

We use the parental responses to the eight hypothetical scenarios to separately calculate the perceived returns to investments at age 5 and the perceived returns to investments at age 10 *for each parent*. In particular, to obtain a measure of individual perceived returns to investments at age 5, ϕ_0, we first calculate the perceived differences in log earnings by comparing a parent's responses in the four scenarios in which age 5 investments are high to the parent's responses in the corresponding four scenarios in which age 5 investments are low, and average across these differences. Therefore,

$$\phi_0 = \frac{(\log \tilde{y}_3 - \log \tilde{y}_1) + (\log \tilde{y}_4 - \log \tilde{y}_2) + (\log \tilde{y}_7 - \log \tilde{y}_5) + (\log \tilde{y}_8 - \log \tilde{y}_6)}{4}. \tag{8}$$

We apply the same procedure to calculate individual perceived returns to late investments:

$$\phi_1 = \frac{(\log \tilde{y}_2 - \log \tilde{y}_1) + (\log \tilde{y}_4 - \log \tilde{y}_3) + (\log \tilde{y}_6 - \log \tilde{y}_5) + (\log \tilde{y}_8 - \log \tilde{y}_7)}{4}. \tag{9}$$

In Section 5.1 we combine estimates of ϕ_0 and ϕ_1 with information on child and parental characteristics and parental investments to obtain estimates of the investment function. Moreover, we can compare parents' perceived returns to estimated returns using the BCS and a reduced form simplification as in:

$$\log \tilde{y}_i j = \alpha + \beta_0 I_{0j} + \beta_1 I_{1j} + \beta_2 \theta_{0j} + \gamma_i + \epsilon_{ij}, \tag{10}$$

where $\tilde{y}_{ij}$ is parent i's belief about the future earnings of the child in scenario j, α is the intercept, I_{0j} and I_{1j} denote the levels of investments in scenario j at age 5 and at age 10, respectively, θ_{0j} refers to the initial human capital level of the child in the scenario, and γ_i are parent fixed effects. The coefficient β_0 provides information on how parents perceive the returns to a one-standard-deviation increase in investments at age 5, while the coefficient β_1 provides information on how parents perceive the returns to a one-standard-deviation increase in investments at age 10. We estimate this empirical specification in Section 6.2.

5. Results

We follow the identification and estimation strategy outlined in Appendix A. The estimation proceeds in two steps. First, we estimate the investment function using our survey data, which allows us to establish how beliefs map into investments. Second, we use the BCS to pin down how investments map into skills and how skills map into adult outcomes. Then, by combining the two steps, we can simulate how changes in beliefs map into changes in outcomes. In all estimations standard errors and confidence intervals are obtained through bootstrapping.

5.1. *The Investment Function*

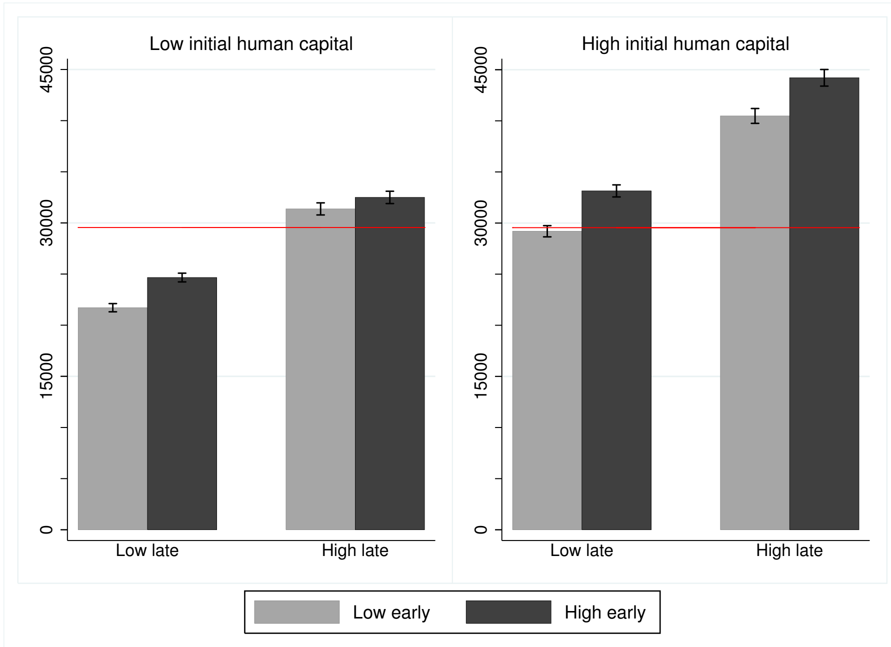
In the following, we first compute perceived returns for each individual parent and then compute how beliefs map into investments using our collected data.

5.1.1. Determining Individual Perceived Returns

Before estimating the investment function, we use parental responses to the hypothetical scenarios in order to back out perceived returns to investments ϕ_0 and ϕ_1. In Figure 1, we present average predicted labor earnings as reported by parents under the different hypothetical scenarios. The left and right panels display predicted earnings for a child with low and high initial human capital, respectively. The red line represents the actual average male earnings conditional on full-time employment at age 30 in 2014. We can tell that parents, on average, make predictions that are comparable to what we observe in the data. We also learn from the figure that parents perceive low early and high late investments to lead to higher earnings at age 30 than high early and low late investments. This perception is confirmed by Figure 2, where we display the kernel densities of individual perceived returns as computed in equations (8) and (9) for parents from the bottom (solid line) and top (dashed line) income quartile. Moreover, compared to parents in the bottom income quartile, parents in the top income quartile perceive the returns to age 5 investments to be significantly higher. We find no significant difference for the perceived returns to age 10 investments.[25]

[25]For a detailed discussion we refer to Boneva and Rauh (2016).

Figure 1. : Mean predicted earnings at age 30 under different scenarios



Note: The figure depicts the expected earnings of a child at age 30 in each of the eight hypothetical investment scenarios averaged across all respondents (with 95% confidence interval). The red line represents the actual average for a 30 year old male conditional on full-time employment in England in 2014 computed using the FRS 2013-2014. This figure is adopted from Boneva and Rauh (2016).

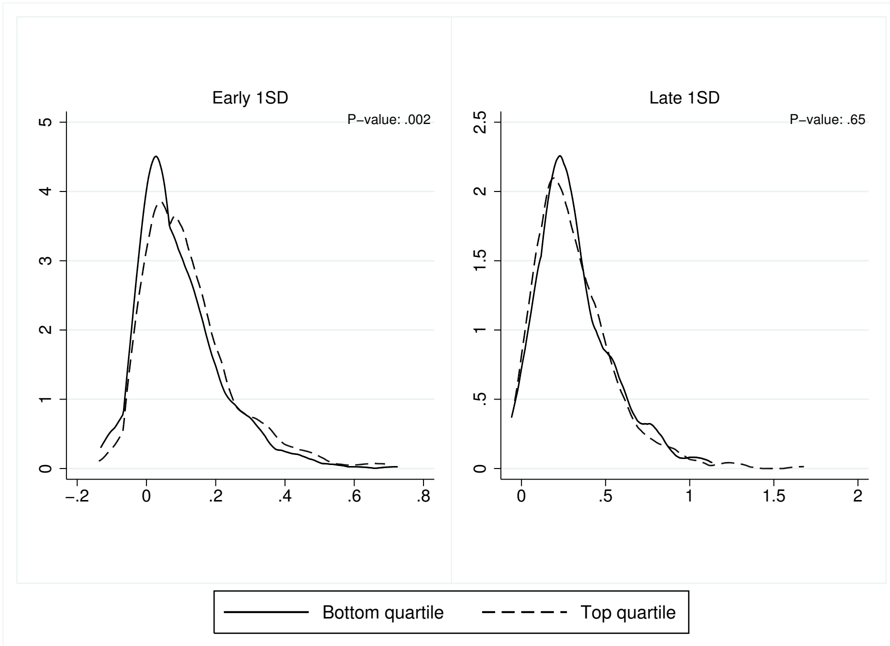
5.1.2. Estimating the Investment Function with Beliefs

Now that we have backed out the perceived returns of parents, we can relate them to reported investments. The investment function takes a 'reduced-form' as in equation (3). All measures are normalized to have mean 0 and a standard deviation of 1 except for time investments at age 5.[26]

To estimate the investment function using our survey data we follow steps 1-6 as outlined in Appendix A2 (Agostinelli and Wiswall, 2016*a*). Given that the survey data contains information on parental beliefs as well as investments, we can identify the role parental beliefs

[26]For time investments at age 5, we have the exact same information in the BCS as in our survey. Other measures are standardized in order to make the measures comparable across surveys.

Figure 2. : Individual perceived returns by parental income quartile



Note: The left panel displays the kernel density of individual average beliefs about returns to investments at age 5, ϕ_0, and the right panel displays the kernel density of investments at age 10, ϕ_1. The solid line is for parents from the bottom income quartile while the dashed line from the top income quartile. For the left panel the Kolmogorov-Smirnov test rejects the null of equality of the two distributions (p-value = .002), whereas for the right panel it does not (p-value = .65). This figure is adopted from Boneva and Rauh (2016).

play in the time investment decision. We separately estimate function (3) for investments at age 5 using the sample of parents with children aged 3-9, and for investments at age 10 using the sample of parents with children aged 10 and above. The results are presented in Table 9, where the first column presents estimates for investments at age 5 and the second column presents estimates for investments at age 10.[27] In order to avoid distortion of the results through outliers, we drop the top and bottom 1% of perceived returns for both periods. Due to the absence of further measures, parents' cognitive skills and parental beliefs are assumed

[27]In Appendix Table E14, we weigh the sample to correct for the sampling bias. Beliefs remain significant and quantitatively important.

to be measured without error in this estimation. The log-log form of the investment equation allows the interpretation of the parameter estimates as elasticities. For instance, a 1% increase in cognitive skills at age 5 increases investments by 0.455%.

Table 9—: Investment function for time (survey)

Parameter	Age 5-9	Age 10-15
θ^C	.232	.093
SE	(.052)	(.025)
95% CI	[.13, .334]	[.044, .142]
θ^{NC}	.135	.252
SE	(.063)	(.031)
95% CI	[.012, .258]	[.191, .313]
P^C	.005	.023
SE	(.027)	(.011)
95% CI	[-.048, .058]	[.001, .045]
P^{NC}	.265	.27
SE	(.067)	(.029)
95% CI	[.134, .396]	[.213, .327]
Male	-.148	-.006
SE	(.057)	(.026)
95% CI	[-.26, -.036]	[-.057, .045]
ϕ	.511	.367
SE	(.222)	(.049)
95% CI belief	[.076, .946]	[.271, .463]
Shock	.15	.262
N	224	1,454

Datasource: Own survey.
Notes: The table exhibits the results from estimating equation (3). Standard errors and 95% confidence intervals are obtained through bootstrapping. ϕ are beliefs about returns.

We find that investments are reinforcing in terms of the stocks of cognitive and noncognitive skills. Moreover, we find that investments are highly responsive to beliefs about returns to investments, in particular for early investments. A one percentage point increase in perceived returns increases investments by 0.51% for early and by 0.37% for late investments. Given that perceived early returns are positively related to household income, beliefs could be a potential source of the relatively high intergenerational earnings persistence in the UK.[28] As also documented in Cunha, Elo and Culhane (2013), ceteris paribus, boys receive less investments than girls.

5.2. *Skill Production and Adult Outcomes*

From the previous section we have learnt how beliefs affect investments. In the following, we use the BCS to shed light on how investments map into skills and then how skills at the end of childhood map into adult outcomes.

5.2.1. Estimating the Skill Production Function Using the BCS

The production of cognitive and noncognitive skills is assumed to depend on a child's stock of skills and parental investments. We present the estimates of the cognitive and noncognitive skill production functions (1) and (2) in Table 10. The first two columns refer to the production of cognitive and the last two to the production of noncognitive skills.[29] For each skill dimension the first column refers to the effect inputs at age 5 have on skills at age 10, whereas the second column displays the effect of inputs at age 10 on skills at age 16.

We find that the stock of a skill is the most important determinant of the same skill in the following period, both for cognitive and noncognitive skills. For instance a 1% increase in cognitive skills at age 5 increases cognitive skills at age 10 by 0.67%. Moreover, the stock of the other skill is an important determinant as well. This indicates that cognitive and noncognitive skills mutually reinforce each other over the course of childhood. Concerning investments, we find that they are of significant importance for both skills in both periods with no evidence of earlier investments dominating vis-à-vis later investment in terms of effectiveness. If anything, the results suggest a greater responsiveness of noncognitive skills to investments at age 10, though the coefficients are statistically indistinguishable. We also

[28]See Corak (2013) for a cross-country comparison of estimates of intergenerational earnings persistence.

[29]The estimation technique outlined in Appendix A requires us to estimate an investment function for the BCS data as well. The results of this intermediate step are discussed in Appendix E1.

Table 10—: Production function of cognitive and noncognitive skills (BCS)

	Cognitive skills		Noncognitive skills	
Input	Age 5-9	Age 10-15	Age 5-9	Age 10-15
θ^C	.666	.534	.238	.169
SE	(.027)	(.024)	(.029)	(.025)
95% CI	[.613, .719]	[.487, .581]	[.181, .295]	[.12, .218]
θ^{NC}	.095	.231	.532	.512
SE	(.018)	(.085)	(.021)	(.086)
95% CI	[.06, .13]	[.064, .398]	[.491, .573]	[.343, .681]
I	.239	.235	.23	.319
SE	(.05)	(.051)	(.056)	(.055)
95% CI	[.141, .337]	[.135, .335]	[.12, .34]	[.211, .427]
Shock	.289	.093	.205	.186
N	4,237	4,212	1,243	2,225

Datasource: BCS.
Notes: The table exhibits the results from estimating the skill production technology for cognitive skills as in (1) and noncognitive skills as in (2). Standard errors and 95% confidence intervals are obtained through bootstrapping.

find that the responsiveness of cognitive skills to the stock of noncognitive skills increases in the second period. The findings in Chetty et al. (2014) suggest that skills might indeed be malleable beyond very early childhood. They find that for adolescents, irrespective of age, the magnitude of the effect of neighbourhood exposure on earnings is proportional to the amount of time spent in a neighbourhood. However, whether the exposure acts through an impact on skills or through other channels, such as social networks, remains unknown. The result that at the later stage noncognitive skills respond more to investments than cognitive skills do is in accordance with previous findings that childhood intervention programs act mostly through the malleability of noncognitive skills (e.g., Borghans et al. 2008; Heckman and Kautz 2014).

The production specification allows for non-constant elasticities of substitution between different inputs. Therefore, we can estimate a range of alternative specifications by interacting various inputs with each other. More specifically, we investigate whether (i) higher educated parents' investments are more effective (at the same level of investment) and (ii) returns to investments are higher for children with greater cognitive and/or noncognitive skills. In order to test these hypotheses, we interact investments I_0 and I_1 with P^C and children skills θ^C and θ^{NC} in production function equations (1) and (2). The results for the production of cognitive and noncognitive skills are presented in Appendix Table E4 and Table E5, respectively, in which for each tested hypothesis the first column refers to period 1 and the second column to period 2. The first two columns investigate whether for a given investment more educated parents the effect is greater. We find that we cannot reject the null of equal effectiveness of investments across parental cognitive skills. This might be a surprise to some as many models in the literature assume that more educated parents invest more effectively (e.g., Becker et al. 2015). This suggests that the widening of the skill (or test-score) gap over the course of childhood between children from weaker versus stronger socio-economic backgrounds may not be attributable to differential quality of parental time investments, but rather to differences in the quantity invested.

Next we try to find out whether our data supports the idea of higher returns to investments when allocated to children with a greater stock of skills. We therefore include the interactions of both θ^C and θ^{NC} with investments in the estimation. For both skills the results again do not allow us to reject the null of no interaction effect, suggesting that a given level of investment operates independent of the initial skill level. We further test this hypothesis by including only one of the two skill dimensions interacted with investments with the same qualitative result. Summarizing, neither for cognitive nor for noncognitive skills do we find significant evidence that the effectiveness of investments differs across parents or initial skills, i.e. all parents are in possession of the same production technology. Therefore, we cannot reject that skill production takes the form of a Cobb-Douglas production function.

5.2.2. Estimating Adult Outcomes Using the BCS

The last part of the production chain we are missing is how skills at the end of childhood translate into adult outcomes over the lifecycle. We estimate how skills map into adult outcomes using equation (6). We look at a range of pecuniary and non-pecuniary adult outcomes at several points over the lifecycle. The descriptive statistics of outcomes are presented in Appendix Table E3. The results for the impacts of cognitive and noncognitive skills are summarized in Appendix Tables E6 and E7, respectively, while the intercept and the effects of the male dummy can be found in Appendix Tables E8 and E9, respectively. In terms of pecuniary outcomes, we estimate the effect of skills and gender on yearly income, hourly income, as well as yearly income conditional on being in full-time employment. Other labor market outcomes investigated are the likelihood of employment and unemployment, and, conditional on employment, the number of hours worked. Finally, we also look at the effects on self-reported life satisfaction on a discrete scale of 1 to 10, the probability of being married, and the probability of smoking daily. We observe most of these outcomes at ages 21, 26, 30, 34, 38, and 42. For an overview of the effects of cognitive and noncognitive skills at different ages, we present Figures 3 and 4, respectively, which display the magnitude of the coefficient together with the 95% confidence interval.[30] For the estimates at age 21, standard errors are larger because of a smaller sample. All monetary values are expressed in real 2015 UK pounds.

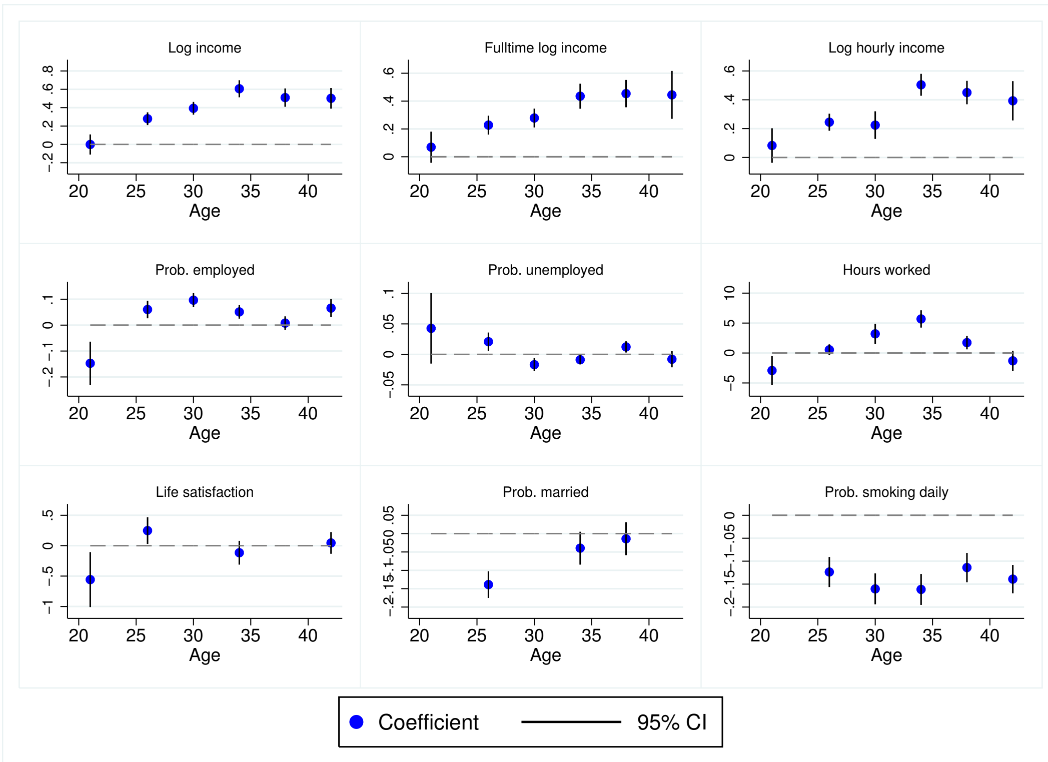
We find that the payoff to cognitive skills in terms of log yearly income increases steadily until it peaks at age 34 followed by a very benign drop. At its peak, a 1% increase in cognitive skills increases earnings by 0.6%. Similar patterns emerge for log hourly income, whereas for log yearly income conditional on full-time employment the return remains constant after age 34. This indicates that cognitive skills at age 16 have a lasting effect on earnings over the lifecycle.

For the probability of employment, cognitive skills have a significant negative impact at age 21, probably stemming from the fact that the more able are more likely to remain in full-time education, and therefore might not yet be working at age 21. In the following years cognitive skills have a slightly positive effect on employment. For unemployment the coefficients of cognitive skills oscillate close to zero over the lifecycle. Hours worked follow a hump-shaped relationship starting and ending just below zero, but exhibiting a significant positive impact in between.

Self-reported life satisfaction has been interpreted as experienced utility (Kahneman, Wakker and Sarin 1997). In our estimation, the impact of cognitive skills on self-reported life sat-

[30]For binary outcomes we estimate a linear probability model.

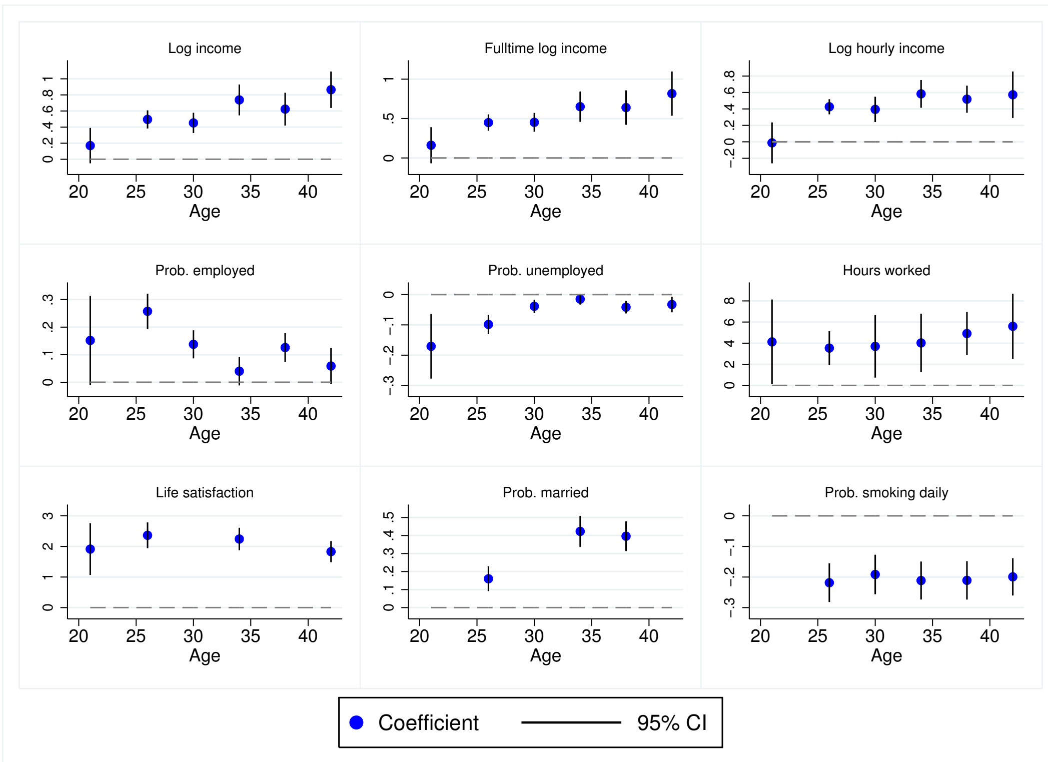
Figure 3. : Effects of cognitive skills over the lifecycle



Datasource: BCS.
Note: The figure displays coefficients $\alpha_{1Q,l}$ of cognitive skills with 95% confidence intervals estimated as in equation (6), the function mapping skills at the end of childhood into outcomes over the lifecycle. The titles indicate the outcome while the x-axis specifies the age at which the outcome is measured.

isfaction over the lifecycle appears ambiguous. While initially the effect seems to be large and negative, it later hovers close to zero. For marriage it appears that people with higher cognitive skills transition into marriage at older ages as the large gap at age 21 is nearly closed by age 34. Finally, the effect of cognitive skills on the probability of smoking daily seems strongly negative and stable over the lifecycle.

Figure 4. : Effects of noncognitive skills over the lifecycle



Datasource: BCS.
Note: The figure displays coefficients $\alpha_{2Q,l}$ of noncognitive skills with 95% confidence intervals estimated as in equation (6), the function mapping skills at the end of childhood into outcomes over the lifecycle. The titles indicate the outcome while the x-axis specifies the age at which the outcome is measured.

For the effect of noncognitive skills on yearly and hourly earnings, the patterns are similar to the effect of cognitive skills. However, for the probability of (un)employment the results suggest a starker impact. The effect on employment is initially strongly positive, though noisy at age 21, before it decreases to slightly above zero by age 34, while the converse effect is observed for unemployment. For hours worked, the effect is large, positive, and fairly constant over the lifecycle. In contrast to cognitive skills, noncognitive skills have a large and positive effect on self-reported life satisfaction over the entire lifecycle. Also for the probability of marriage, noncognitive skills increase the likelihood substantially, with the coefficient increasing considerably between ages 26 and age 34. For the probability of smoking daily, we observe a similar but slightly stronger negative effect than for cognitive skills.

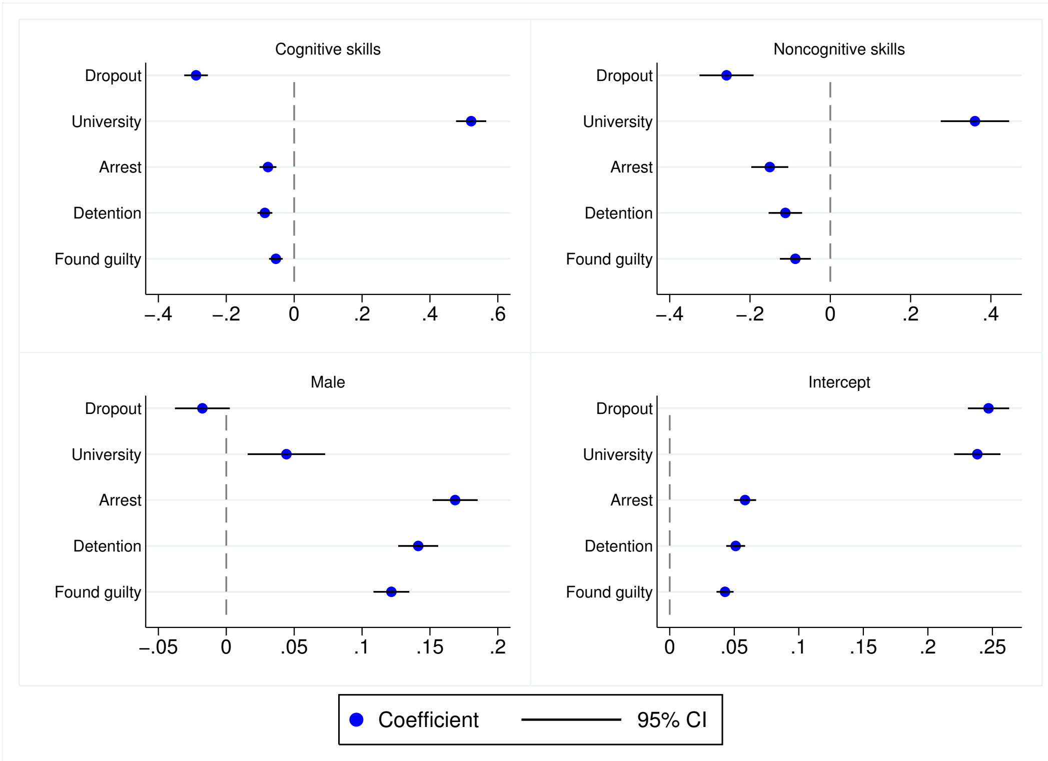
In Appendix Figure E.1, we plot the intercept of adult outcomes over the lifecycle. Strikingly, for both income and income conditional on working full-time, the intercept is constant over the lifecycle. This suggests that lifecycle profiles in earnings could be attributable to cognitive and noncognitive skills.

For some outcomes, we only have measures at one point in time either because we interpret the outcome as constant as of a certain age (i.e. being a school dropout or university graduate) or because we only observe the outcome at one point in time in the data. The estimates for these outcomes are exhibited in Figure 5 and in Appendix Figure E.2.

We find that both cognitive and noncognitive skills have a large negative effect on the probability of dropping out of school, and a large positive effect on the probability of graduating from university. The propensities of arrest, detention, and having been found guilty by a court are negatively affected by both cognitive and noncognitive skills alike. Concerning marriage, the regret of being married to one's spouse and the spouse's income at age 42 are not affected by cognitive skills. However, higher noncognitive skills are negatively associated with the regret of being with one's partner and strongly positively with the spouse's income.

In order to investigate whether returns to skills differ by gender, we run the same specifications while including interaction terms between the male dummy and cognitive and noncognitive skills. In Appendix Figures E.3 and E.4, we plot the coefficient of the interaction term between skills and the male dummy. Indeed, we find that log income responds less to cognitive skills for males than for females. However, this seems to be driven by the response of the intensive margin of labor supply to cognitive skills, which is greater for females, rather

Figure 5. : Determinants of adult outcomes measured at age 30



Note: The figure displays coefficients $\alpha_{Q,l}$ with 95% confidence intervals estimated as in equation (6), the function mapping skills at the end of childhood into outcomes at age 30. Arrest and detention into police custody refer to whether respondent experienced these events within past 10 years. The titles indicate the independent while the y-axis specifies the dependent variables.

than differences in the responsiveness of hourly wages, which seem to respond equally for males and females. Other than these effects, we do not find much evidence that responses to skills differ by gender. Now that we have estimated the entire chain, i.e. how beliefs map into investments, how investments map into skills, and how skills map into adult outcomes, through simulations we can gain an understanding of how beliefs affect into adult outcomes.

6. Simulations

Using the estimates of the investment and skill production functions, we can simulate a range of counterfactuals, including the consequences on aggregate outcomes and distributional effects caused by shifts in parental beliefs. The synthetic samples we draw come from the variance–covariance matrices of the initial distributions presented in Appendix Tables E2 and E13 for the BCS and our survey, respectively. For all outcomes, we present the average results of 1,000 Monte Carlo simulations.

6.1. Decomposing the Drivers of Heterogeneity in the Survey Sample

In order to gain a better understanding of the relative importance of initial conditions and inputs, we sequentially assign mean values of each input and initial condition to the entire simulated sample and see how this contributes to the variance in outcomes. More specifically, we equalize time investments I in both periods, parental cognitive and noncognitive skills (which are constant over time), and children's initial cognitive and noncognitive skills.[31]

In Table 11 the first and second column display the benchmark mean and variance, respectively. The top row of the third column displays the variance and the bottom the share of variance accounted for by parental beliefs about returns to education. We find that the heterogeneity in beliefs can account for 1% of the variation in cognitive and noncognitive skills and 2% of the variation in discounted lifetime earnings. Equalizing parental skills reduces the variance in discounted lifetime earnings by 6%, which is fully attributable to parental noncognitive skills. Initial skills of the children are important. Together they account for 37% of the variance, most of which is due to differences in cognitive skills (30%). This indicates that genes and/or very early childhood play a substantial role as well. It is worth noting that time investments and initial skills contribute almost equally to the dispersion in discounted lifetime income.

In Table 12, we repeat the same exercise while instead focusing on the inequality and intergenerational mobility concerning discounted lifetime income. Inequality is captured by the

[31]Concerning the contribution of inputs by period, we refer to Appendix Table E10, where we also break down the results when we only equalize inputs in one of the two childhood periods.

Table 11—: Variance in outcomes explained by inputs

Outcome	Mean	Var.	ϕ	I	Parental skills P^C	P^{NC}	P	Initial conditions θ_0^C	θ_0^{NC}	θ_0
Skills										
$\ln \theta_T^C$	.03	.34	.34	.26	.34	.33	.33	.24	.33	.23
			(.01)	(.22)	(.00)	(.04)	(.04)	(.30)	(.04)	(.34)
$\ln \theta_T^{NC}$	.04	.38	.38	.29	.38	.37	.37	.34	.36	.31
			(.01)	(.24)	(.00)	(.03)	(.04)	(.12)	(.07)	(.20)
Income										
Discounted lifetime	245,820	4.82	4.72	3.15	4.81	4.50	4.49	3.38	4.34	3.02
			(.02)	(.35)	(.00)	(.07)	(.07)	(.3)	(.10)	(.37)
Disc. life. (fulltime)	275,655	4.37	4.29	2.93	4.36	4.10	4.10	3.20	3.97	2.87
			(.02)	(.33)	(.00)	(.06)	(.06)	(.27)	(.09)	(.34)
Labor market										
Hours worked	33.36	42.54	42.37	39.61	42.53	41.97	41.95	39.81	41.64	38.93
			(.00)	(.07)	(.00)	(.01)	(.01)	(.06)	(.02)	(.09)
Education										
University	.35	.11	.11	.09	.11	.11	.11	.09	.11	.09
			(.01)	(.18)	(.00)	(.03)	(.03)	(.16)	(.03)	(.21)
Dropout	.26	.05	.05	.04	.05	.05	.05	.04	.05	.04
			(.01)	(.24)	(.00)	(.04)	(.04)	(.21)	(.05)	(.27)

Datasource: Own survey.
Notes: The columns refer to the input that is equalized in the experiment. For each outcome the top row exhibits the sample variance, and the bottom row in brackets represents the fraction by which the variance has been reduced by equalizing the respective input. Discounted lifetime income is computed from age 26 to 42 by interpolating linearly between available data points and discounted using a 2% annual interest rate. Estimated income at a given age is multiplied with the estimated probability of employment. For discounted lifetime income all variances have to be multiplied by 10^{10}.

Gini coefficient, whereas mobility is summarized by the intergenerational earnings elasticity obtained by regressing the log of children's discounted lifetime income on the log of parental earnings at age 5. We find that the Gini remains unchanged when we equalize beliefs, while earnings persistence reduces by 6%. Both investments and initial skills account for about 10% of earnings inequality in terms of the Gini. For earnings persistence, we find that initial skills are more important, accounting for 81% of the persistence, while differences in time investments account for a comparably low 34%.

6.2. Comparing Perceived and 'True' Returns

In Table 13, we compare the 'true' returns estimated using the BCS to the returns perceived by parents. We estimate the 'true' returns by drawing 100 times a synthetic sample of 100,000

Table 12—: Gini and IGE explained by inputs

	Bench-mark	ϕ	I	Parental skills P^C	P^{NC}	P	Initial conditions θ_0^C	θ_0^{NC}	θ_0
Gini	.42	.42	.38	.42	.42	.42	.39	.41	.38
		(.00)	(.10)	(.00)	(.02)	(.02)	(.08)	(.02)	(.11)
IGE	.46	.43	.3	.45	.41	.4	.28	.28	.09
		(.06)	(.34)	(.01)	(.11)	(.12)	(.39)	(.39)	(.81)

Datasource: Own survey.
Notes: The columns refer to the input that is equalized in the experiment. For each outcome, the top row exhibits the outcome for the benchmark and the different scenarios, while the bottom row in brackets represents the fraction by which the outcome has been reduced by equalizing the respective input. Discounted lifetime income is computed from age 26 to 42 by interpolating linearly between available data points and discounted using a 2% annual interest rate. Estimated income at a given age is multiplied with the estimated probability of employment.

children from the initial conditions Ω as in (4). For each draw, we keep the children at the 30th and 70th percentile of the cognitive skill distribution at age 5, and we consider these as "low" and "high" initial human capital endowments. We then compute earnings for all four scenarios of low/high and early/late investments, i.e. we allocate investments 0.5 standard deviations below and above the mean as low and high investments, respectively. This allows us to compute earnings at age 30 using the estimates from the investment, skill and adult outcome functions. Finally, we regress log earnings at age 30 on early and late investments, initial human capital, a male dummy, and parental cognitive and noncognitive skills, which we, though not in an explicit sense, hold fixed in the scenarios of our own survey. For our own survey we add respondent fixed effects and estimate the reduced form equation (10).

In Table 13 we see that parents' perceived returns to early investments and initial human capital are extremely close to estimated returns from the BCS using the reduced form equation (10). Parents perceive the return of the one-standard deviation increase in early investments to be 10%, while in the data it is 11%. Similarly, the perceived return to high initial skills is 29% compared to 25% in the data. However, late returns are highly overestimated by parents with an expected increase of 32% versus only 17% estimated from the data.

Table 13—: Data estimate versus survey beliefs about returns to time investment

Dependent variable: Log earnings at age 30		
	(Estimate)	(Belief)
Early investments	0.111***	0.100***
	(0.001)	(0.003)
Late investments	0.173***	0.315***
	(0.001)	(0.006)
High human capital	0.250***	0.290***
	(0.001)	(0.006)
Parent fixed effects	No	Yes
Parental controls	Yes	No
Datasource	BCS	Survey
Observations	800,000	15,639
R^2	0.165	0.784

Datasource: BCS and own survey.
Notes: The coefficients displayed result from estimating equation (10). For the BCS, the sample is composed of simulations from 100 draws from a synthetic sample.

6.3. Simulating a Belief Treatment

Next we look at the impact of a shift in parental beliefs. The type of intervention in mind would include informing parents about the malleability of skills and the value of their time investments. Similar in spirit, Alan, Boneva and Ertac (2015) transmit the idea of malleability of skills to children, finding large positive effects on effort and outcomes. In our simulations, we draw a sample of 100,000 individuals from Ω and assign the 'true' returns estimated in Section 6.2 to all parents with beliefs below 'true' beliefs.[32] We simulate the intervention both separately and jointly for early and late investments. This could be interpreted as an intervention targeted at schools where parents are more likely to perceive returns to time investments to be lower.

For earnings and earnings conditional on full-time employment, we compute the cumulative impact over the lifecycle from age 26 to 42, where values are multiplied by the respective (full-

[32]Beliefs of parents above 'true' beliefs remain unchanged. Means and standard errors are computed using Monte Carlo simulations with 1,000 repetitions.

time) employment probabilities and are discounted to age 5 using a 2% discount rate.

As a result of the intervention, about 50% of parents are treated at the early stage and 30% at the late stage, whereas if parents are treated at both stages then nearly 55% receive treatment. In Appendix Figure E.6, we present the cumulative and probability density of the treatment effect for the absolute gains in discounted lifetime income. The average treatment effect in terms of discounted lifetime earnings for an early intervention is £2,483 (standard deviation £4,901) and £4,800 conditional on being treated (SD £5,930), for a late intervention is £1,627 (SD £4,557) and £5,293 conditional on being treated (SD £6,920), and for intervening in both periods is £4,168 (standard deviation £9,158 SD) and £7,838 conditional on being treated (SD £11,332).

In Table 14, we summarize the average gains in absolute and relative terms for a range of outcomes. The first column exhibits the simulated mean without the intervention. Columns (2) and (3) show the absolute and relative aggregate effect, respectively, of increasing early beliefs, columns (4) and (5) for equalizing late, and the last two columns for equalizing both early and late together. Shifting all parents with perceived returns lower than 'true' returns to 'true' beliefs would create a per capita benefit of more than £4,000 (in year 2015 terms) by age 42 when the cumulative gains are discounted to age 5, the moment when the intervention would to take place. The gain in discounted lifetime income is almost 2%. This change can be attributed to an increase in hourly earnings of 1.2%, as well as increases in employment probabilities and hours worked, which both are raised by 0.3% over the lifecycle. Stronger impacts can be expected in terms of educational attainment, with an increase in university degrees of 2.3% and a 2.6% reduction in dropouts. Finally, the share of individuals smoking daily declines by 2.2% in the simulations.

In Figure 6, we see the simulated outcomes by parental income decile at age 5 when increasing beliefs for parents with low perceived returns in both periods. The bars represent the relative gain over the baseline scenario of no intervention. In terms of relative gains, children from financially deprived households have substantially more to gain. However, when looking at gains in absolute terms as shown in Appendix Figure E.5, one can tell that children across the entire parental income distribution could profit from a belief intervention, par-

Table 14—: Effect of increase for parents with beliefs below 'true' beliefs

	Benchmark	Early (ϕ_0)		Late (ϕ_1)		Both	
	Mean	Δ	%	Δ	%	Δ	%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Income							
Discounted lifetime	245,820	2,483	1	1,627	.7	4,168	1.7
Disc. lifetime (full-time)	275,662	2,517	.9	1,669	.6	4,238	1.5
Hourly	14.738	.11	.7	.07	.5	.18	1.2
Labor market							
Employment	.784	.0013	.2	.0008	.1	.0021	.3
Hours worked/week	33.355	.0572	.2	.0369	.1	.0941	.3
Unemployment	.024	-.0003	-1.2	-.0002	-.8	-.0005	-2
Education							
Dropout	.255	-.0041	-1.6	-.0024	-1	-.0064	-2.6
University	.353	.0051	1.4	.0031	.9	.0082	2.3
Health							
Smoking daily	.2	-.0026	-1.3	-.0016	-.8	-.0042	-2.2

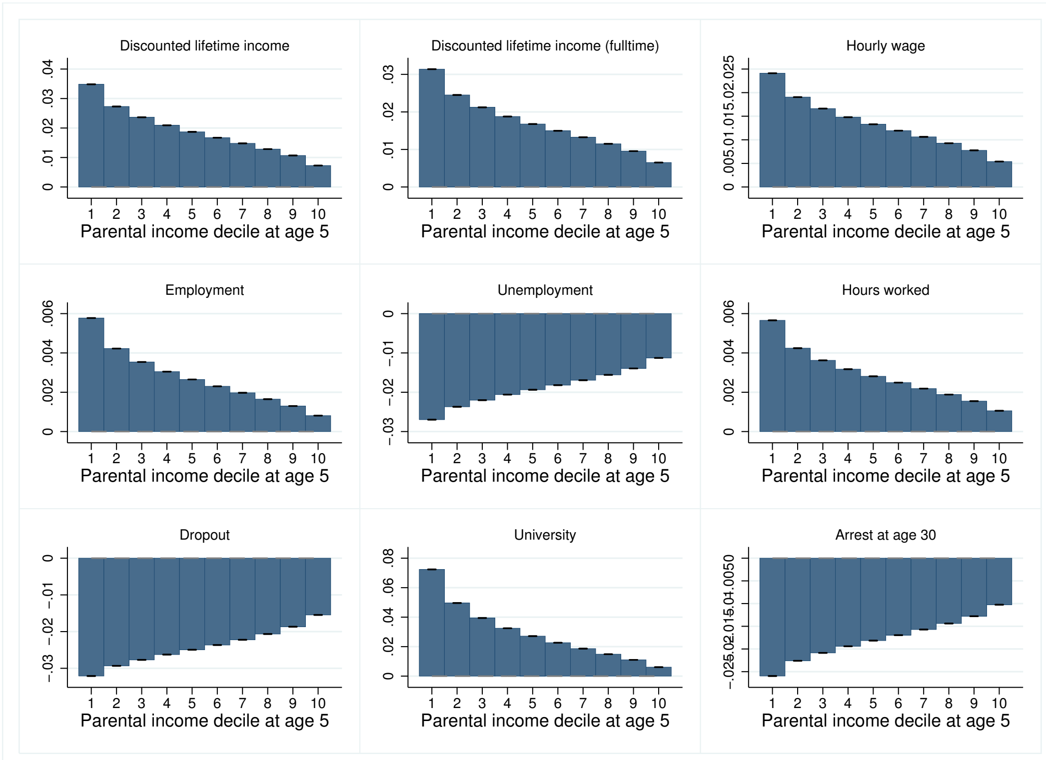
Datasource: Own survey.
Notes: In this simulation parents with perceived returns below 'true' returns are assigned 'true' beliefs. Δ represents the aggregate absolute change, while "%" reflects the aggregate change in terms of percentages. In columns (2) and (3), only early beliefs are shifted, while in columns (4) and (5) only late beliefs are changed. In columns (6) and (7), both beliefs are shifted.

ticularly in terms of earnings. In absolute terms, the gains are more concentrated amongst children from poor households for hours worked and the probabilities of dropping out of school, (un)employment, and arrest.

7. Discussion

Two important questions emerge concerning parental beliefs about the returns to investments in their children. First, we know little about beliefs held by parents but next to nothing about the actual process by which their beliefs are formed. It is possible that beliefs are formed based on information exchanged between parents and observations made in the environment and neighborhood. One could imagine a theoretical model in the spirit of Piketty (1995) in which individuals update their beliefs through their (self-fulfilling) observations. Parents in poor neighborhoods observe neighbors with low returns to investments in education, while in

Figure 6. : Relative gain by parental income decile at age 5



Note: The figure depicts the average relative gain by parental income decile at age 5 of the belief intervention for a range of outcomes. The treatment involves increasing beliefs of parents with perceived returns below the 'true' level to the 'true' level. 95% confidence intervals of the mean effect by decile are computed from 1000 simulations.

rich neighborhoods high returns are observed. If parents update their beliefs based on the observed information, we would observe the correlation between SES and perceived returns. Indeed, we do find that beliefs correlate within schools but cannot rule out selection as a driver of this relation. In Boneva and Rauh (2016), we find very little evidence for updating over time given that perceived returns in the cross-section do not differ systematically by the age of the oldest child, which could be attributable to the persistence of neighborhood and personal environments.

Second, we do not know exactly why parents of lower SES on average believe that returns are lower. The data provides no evidence that indeed their returns are lower. Parents might believe that they themselves are less capable of transmitting skills and/or they might believe that skills are less malleable in general. In Boneva and Rauh (2016), we provide suggestive evidence that perceived returns go hand in hand with beliefs about the malleability of skills. However, we cannot rule out that parental beliefs about limitations of their own capabilities play a role as well.

These questions are important to tackle in order to design an effective belief treatment. Mayer et al. (2015) carry out an intervention with parents using three behavioral tools, i.e. text reminders, goal-setting, and social rewards, and find that the treatment effect is greatest for present-oriented parents. Alan, Boneva and Ertac (2015) design an intervention, in which they convey the idea of malleability of skills and the importance of grit to children, and find considerable effects. One could imagine a similar intervention with parents, which transmits the idea malleable skills to parents and the impact investments can have on a child's future.

8. Conclusion

In this paper, we add to the understanding of the determinants of human capital and its effects in later life. We focus, in particular, on the role of parental beliefs about returns to time investments. In order to do so, we combine two datasources, the British Cohort Study and survey data we collect ourselves. We use the collected data to estimate how parental beliefs affect investments into their children. The survey uses hypothetical scenarios which allow us to isolate parental beliefs about particular investments; these investments coincide with those in the BCS. Exploiting the rich panel structure of the BCS, we estimate a dynamic latent factor model of human capital accumulation and further estimate how skills map into adult outcomes over the lifecycle. In our estimation strategy we take into account that measures are scaled arbitrarily and are measured with error. Finally, we combine these estimates to conduct simulations in order to decompose which inputs contribute most to the heterogeneity in outcomes and to conduct counterfactual experiments involving belief interventions.

Our estimates suggest that all parents are equipped with the same production technology in terms of effectiveness of investments, but differ in terms of their beliefs about it. Though initial human capital at age 5 is the most important input, we still find that time investments by parents explain more than one-third of the variation of discounted lifetime earnings. Moreover, we find that the heterogeneity in late investments contributes more to differences in outcomes than the heterogeneity in early investments. We also find that beliefs are predictive of investments. Shifting all parents with below-true beliefs to true beliefs is estimated to lead to a gain of nearly £8,000 for children of treated parents and 1.7% of total discounted lifetime income.

Our results suggest that belief treatments could be an effective way to address inequality of opportunity.[33] While the combination of the two datasets is a contribution in itself, future research would profit from detailed information about parental beliefs within panel datasets. It is important for academics and policymakers to gain a better understanding of the role played by parental beliefs in order to design effective intervention studies.

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[33]We can make no statements about efficiency as we have no cost estimates of a belief treatment.

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Appendix A: Identification and Estimation

A1. Identification

Our identification follows the arguments of Agostinelli and Wiswall (2016*a*). For completeness, we summarize those arguments below. In particular, we assume that measurement errors are contemporaneously independent across measures and independent over time. Moreover, we assume that measurement errors in any period are independent of the latent investments and cognitive and noncognitive skills in any time period.

Measurement Model Assumptions:

1) $\epsilon_{t,m} \perp \epsilon_{t,m'}$ *for all* t *and* $m \neq m'$

2) $\epsilon_{t,m} \perp \epsilon_{t',m'}$ *for all* $t \neq t'$ *and all* m *and* m'

3) $\epsilon_{t,m} \perp I_{t'}$ *for all* t *and* t' *and all* m

4) $\epsilon_{t,m} \perp \theta_{t'}^{C}$ *for all* t *and* t' *and all* m

5) $\epsilon_{t,m} \perp \theta_{t'}^{NC}$ *for all* t *and* t' *and all* m

Under Assumption 1 and Normalization 1, the factor loadings in the initial time period, $\lambda_{0,2}, \ldots, \lambda_{0,M_0}$, can be identified from the ratios of measurement covariances as long as there are at least three measures for each factor:

$$\lambda_{0,m} = \frac{Cov(Z_{0,m}, Z_{0,m'})}{Cov(Z_{0,1}, Z_{0,m'})}$$

Moreover, under the normalization $E[\ln \omega_0] = 0$, we can identify the intercepts of the measurements:

$$\mu_{0,m} = E[Z_{0,m}]$$

The Kotlarski Theorem can then be applied to the residual measures $\widetilde{Z}_{0,m}$ defined as:

$$\widetilde{Z}_{0,m} = \frac{Z_{0,m} - \mu_{0,m}}{\lambda_{0,m}}$$

Conditional on the level of investment, I_0, the distribution of θ_0^C and θ_0^{NC} can be identified for any level of investment, I_0. This then enables the identification of the joint distribution of latent skills and investments in the initial period, $G_0(I_0, \theta_0^C, \theta_0^{NC})$, up to the initial normalization.

The identification of the production function proceeds sequentially (Agostinelli and Wiswall, 2016*a*). To identify the full sequence of production technologies, the following minimal data is required. First, at least three measures of each latent factor are needed for the initial time period. Second, in each of the following time periods, there needs to be at least one measure for each latent skill. By applying appropriate transformations to the data, the parameters of the production technology can be identified without knowledge of the measurement parameters in period $t+1$. The estimation steps are described in detail in Section A2.

A2. Estimation

We use the estimation algorithm developed in Agostinelli and Wiswall (2016*a*) to estimate the model. The estimation proceeds in several steps.

Step 1: First, we estimate the initial measurement parameters. More specifically, for each factor $\omega \in \{\theta^C, \theta^{NC}, P^{NC}\}$, we have three measures $m \in \{1, 2, 3\}$ in the initial period $t = 0$:

$$Z_{\omega,0,m} = \mu_{\omega,0,m} + \lambda_{\omega,0,m} \ln \omega_0 + \epsilon_{\omega,0,m}.$$

We assume that the log-factors are mean 0 in the initial period, which allows us to identify the intercepts of the measurements:

$$\mu_{\omega 0m} = E[Z_{\omega 0m}] \, \forall m \; and \; \forall \omega.$$

Moreover, for each latent factor, the factor loading on the first measure ($m = 1$) is normalized to 1, i.e. $\lambda_{\omega,0,1} = 1 \, \forall \omega$. We obtain the other factor loadings $\lambda_{\omega 0m}$ from the ratio of covariances between the different measurements:

$$\lambda_{\omega 0m} = \frac{Cov(Z_{\omega 0m}, Z_{\omega 0m'})}{Cov(Z_{\omega 01}, Z_{\omega 0m'})} \, \forall m' \neq m.$$

While we assume that the level of the child's cognitive and noncognitive skills, the parent's noncognitive skills and investments are measured with error, we assume that the parent's cognitive skills, parental beliefs and household income are measured without error. The vector of initial conditions is given by:

$$\Omega = (\ln \theta_0^C, \ln \theta_0^{NC}, \ln P^C, \ln P^{NC}, \ln \phi).$$

The initial conditions are assumed to be jointly normally distributed:

$$\Omega \sim N(\mu_\Omega, \Sigma_\Omega),$$

where μ_Ω is the vector of means, and Σ_Ω is the variance-covariance matrix. The diagonal elements of the variance-covariance matrix Σ_Ω can be obtained as follows:

$$Var(\ln \omega_0) = \frac{Cov(Z_{\omega 01}, Z_{\omega 02}) \cdot Cov(Z_{\omega 01}, Z_{\omega 03})}{Cov(Z_{\omega 02}, Z_{\omega 03})}.$$

The off-diagonal elements can be calculated as follows:

$$Cov(\ln \omega_0^A, \ln \omega_0^B) = Cov(Z_{\omega 01}^A, Z_{\omega 01}^B)$$

Finally, we also calculate the 'residual' measures $\widetilde{Z}_{\omega 0m}$:

$$\widetilde{Z}_{\omega 0m} = \frac{Z_{\omega 0m} - \mu_{\omega 0m}}{\lambda_{\omega 0m}} \, \forall \omega \; and \; \forall m$$

Step 2: Second, we estimate the parameters of the investment function. Investments are also measured with error and there are three measurements:

$$Z_{I0m} = \mu_{I0m} + \lambda_{I0m} \ln I_0 + \epsilon_{I0m} \; \forall m.$$

Re-arranging, $\ln I_0$ can be written as:

$$\ln I_0 = \frac{Z_{I0m} - \mu_{I0m} - \epsilon_{I0m}}{\lambda_{I0m}}$$

Using the fact that $\ln \omega_0 = \widetilde{Z}_{\omega 0m} - \frac{\epsilon_{\omega 0m}}{\lambda_{I0m}}$, we substitute into the investment function, and re-arrange for Z_{I0m}:

$$\begin{aligned} Z_{I0m} &= \mu_{I0m} + \lambda_{I0m}(\alpha_{10}\widetilde{Z}_{\theta^C 0m} + \alpha_{20}\widetilde{Z}_{\theta^{NC} 0m} + \alpha_{30} \ln P^C + \alpha_{40}\widetilde{Z}_{P^{NC} 0m} + \alpha_{50} \ln \phi_0) + \pi_{I0m} \\ &= \beta_{00m} + \beta_{10m}\widetilde{Z}_{\theta^C 0m} + \beta_{20m}\widetilde{Z}_{\theta^{NC} 0m} + \beta_{30m} \ln P^C + \beta_{40m}\widetilde{Z}_{P^{NC} 0m} + \beta_{50m} \ln \phi_0 + \pi_{I0m} \end{aligned}$$

Estimating this equation using least squares will yield inconsistent estimates because the residual factors are correlated with the error term. To estimate this equation consistently, we use an instrumental variables approach in which we instrument the residual measurements of each latent factor with all other available measurements for this latent factor $Z_{\omega 0m'}$. Once all β's are estimated, we can uncover the α's from the following equation:

$$\alpha_{j0} = \frac{\beta_{j0m}}{\sum_{j=1}^{5} \beta_{j0m}}.$$

Step 3: We can now calculate the measurement parameters for latent investment:

$$\mu_{I0m} = \beta_{00m},$$

$$\lambda_{I0m} = \sum_{j=1}^{5} \beta_{j0m}.$$

Again we can also compute the 'residual' measures for investment:

$$\widetilde{Z}_{I0m} = \frac{Z_{I0m} - \mu_{I0m}}{\lambda_{I0m}} \ \forall m.$$

Step 4: Next we estimate the parameters of the two production functions. Substituting and re-arranging yields the following specification for skill $\theta \in \{\theta^C, \theta^{NC}\}$:

$$Z_{\theta 1m} = \delta_{00m} + \delta_{10m}\widetilde{Z}_{\theta^C 0m} + \delta_{20m}\widetilde{Z}_{\theta^{NC} 0m} + \delta_{30m}\widetilde{Z}_{I0m} + \pi_{\theta 0m}$$

where $\delta_{00m} = \mu_{\theta 1m}$ and $\delta_{j0m} = \lambda_{\theta 1m}\gamma_{j0}$. Again, least squares yields inconsistent estimates so we use an instrumental variables strategy to estimate this equation, where the residual measurements of each factor are instrumented with the alternative measurements $Z_{\omega 0m'}$.

We can then recover the structural parameters:

$$\gamma_{j0} = \frac{\delta_{j0m}}{\sum_{j=1}^{3} \delta_{j0m}}.$$

Step 5: We can now compute the measurement parameters of cognitive and noncognitive skills in period $t+1$ from the respective regression coefficients:

$$\mu_{\theta 1m} = \delta_{00m},$$

$$\lambda_{\theta 1m} = \sum_{j=1}^{3} \delta_{j0m}$$

This step is repeated twice, once for cognitive and once for noncognitive skills.

Step 6: Finally, we can estimate the variance of the shocks to investments and to cognitive and noncognitive skill production.

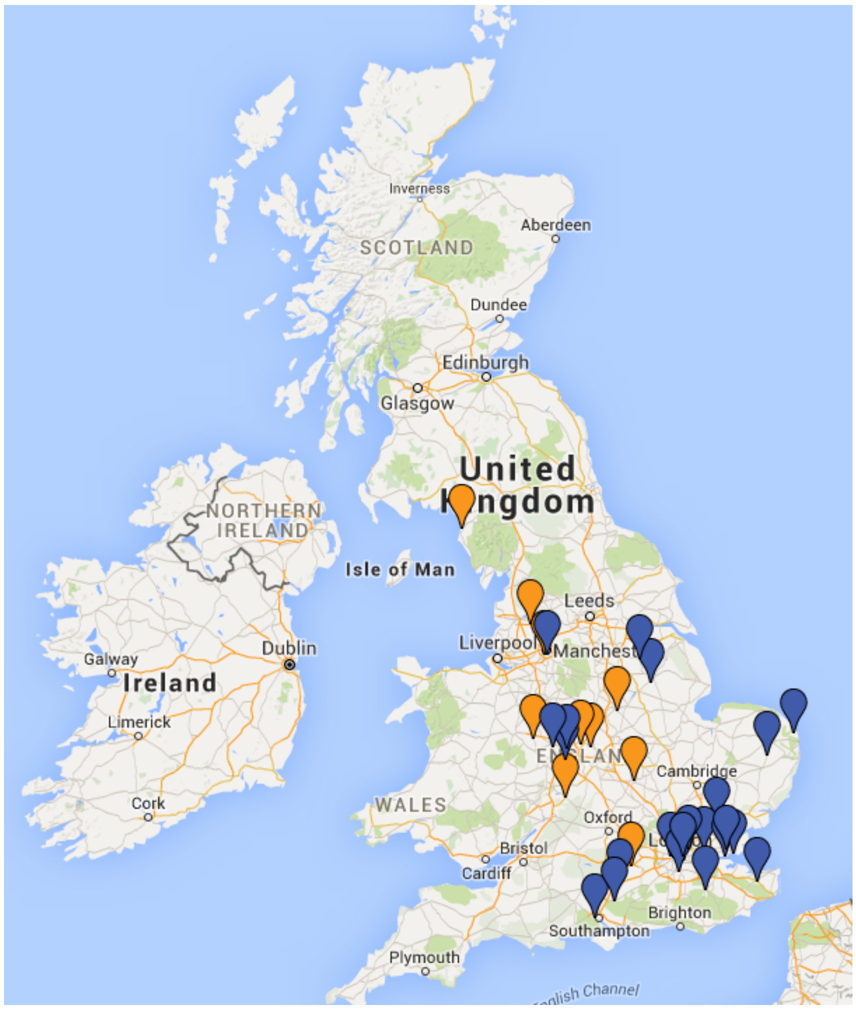
$$Cov(\frac{\pi_{I0m}}{\lambda_{I0m}}, \widetilde{Z}_{I0m'}) = \sigma^2_{I0}$$

$$Cov(\frac{\pi_{\theta 1m}}{\lambda_{I1m}}, \widetilde{Z}_{\theta 1m'}) = \sigma^2_{\theta 0}$$

As in the previous step, this step needs to be repeated for both skill dimensions, i.e. cognitive and noncognitive.

Appendix B

Figure B.1. : Map of schools in collected data (orange=primary, blue=secondary)



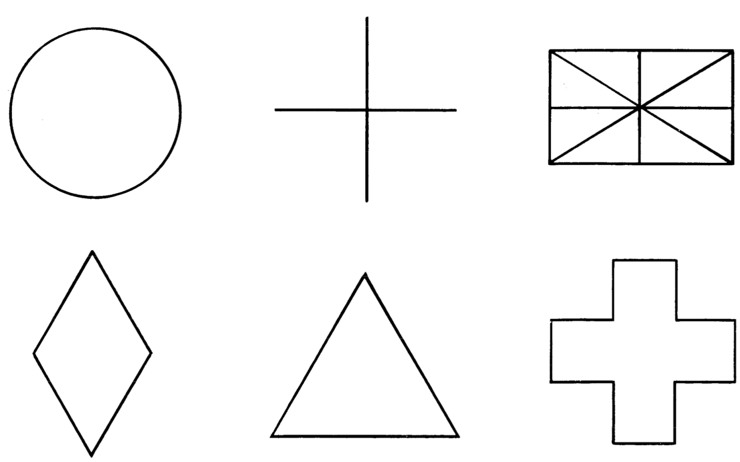
Appendix C: Measures in BCS

Table C1—: Sample of parental noncognitive skills questions

Malaise questions
Do you often feel depressed?
Do you get easily upset or irritated?
Do you often feel rushed during the day?
Do you usually have great difficulty in falling or staying asleep?
Do you often get into a violent rage?
Do you suddenly become scared for no good reason?
Have you ever had a nervous breakdown?
Locus of control
I can do things as well as most my age.
I am a useful person to have around.
I haven't got much to be proud of.
I sometimes think I am no good at all.
I feel I am as good as anybody else.
I am not really getting anywhere in life.

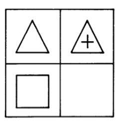
C1. Children skills

Cognitive skills



The vocabulary score is derived from a test in which names of objects are read out loud and a child then has to point to a picture of the object. Examples of objects include drum, parachute, fence, or goat. The test is stopped when 5 consecutive errors occurred.

The British Ability Score is a composite of children's performance in four tasks. The first task includes writing definitions of words such as sport, travel, splash, or army. In the second task, a child has to read digits out loud from a list. In the third task, children are presented three things and are asked to think of something similar. If the response is correct, children are ask why they go together. Examples include orange, strawberry, banana or mosque, chapel, synagogue. The fourth task involves completing matrices such as the following one:



Noncognitive skills

Table C2—: Sample of children's noncognitive skills questions

Rutter scale	
Very restless, often running about or jumping up and down.	
Often destroys own or others property.	
Frequently fights with other children.	
Often worried, worries about many things.	
Is often disobedient.	
Cannot settle to anything for more than a few moments.	
Locus control	
Age 10	Age 16
Not worth trying hard?	Nice things happen to you-only good luck?
Wishing hakes good things happen?	Get into argument-usually others' fault?
High mark is a matter of luck?	Studying for tests is a waste of time?
Self confidence	
Positive	Negative
I am friendly.	I am bored.
I am clever.	I am lazy.
I am independent.	I am shy.

Appendix D: Survey Questionnaire

D1. Hypothetical Scenarios

We are interested in your opinion about the importance of different parenting practices. For this purpose, we will ask you to imagine two different families, the Jones and the Smiths, who make decisions about how involved they should be in their child's upbringing. We know these questions are difficult. Please try to consider each scenario carefully and tell us what you believe the likely outcome to be.

Mr and Mrs Jones have one child, John. John is 5 years old, and he is <u>more intelligent</u> than the average kid. On an intelligence test, he scored better than 70% of the kids in his age group. Now let's think about the future earnings of John. Assuming that John is working full-time, what do you expect John's gross yearly earnings to be when he is 30 years old in each of the following scenarios:

A) If at age 5 the parents read to John <u>every second day</u>, they <u>rarely</u> take John to the playground and John watches TV for <u>2 hours</u> every day, and at age 10 the parents show <u>moderate</u> interest in John's education, they <u>don't talk to John very much</u>, and they <u>sometimes</u> engage in activities together (e.g. go out for walks, have breakfast or tea together).

B) If at age 5 the parents read to John <u>every day</u>, they take John to the playground <u>once every fortnight</u>, and John watches TV for <u>1 hour</u> every day, and at age 10 the parents show <u>moderate</u> interest in John's education, they <u>don't talk to John very much</u>, and they <u>sometimes</u> engage in activities together (e.g. go out for walks, have breakfast or tea together).

C) If at age 5 the parents read to John <u>every day</u>, they take John to the playground <u>once every fortnight</u>, and John watches TV for <u>1 hour</u> every day, and at age 10 the parents show <u>a lot</u> of interest in John's education, they talk to John <u>quite a lot</u>, and they <u>often</u> engage in activities together (e.g. go out for walks, have breakfast or tea together).

D) If at age 5 the parents read to John every second day, they rarely take John to the playground and John watches TV for 2 hours every day, and at age 10 the parents show a lot of interest in John's education, they talk to John quite a lot, and they often engage in activities together (e.g. go out for walks, have breakfast or tea together).

Now imagine a different family, the Smiths. In many respects the Smiths are very similar to the Jones. For example, Mr and Mrs Smith also have one child, Simon, who is also 5 years old. They live in the same neighbourhood as Mr and Mrs Jones and they have similar levels of income and education. However, there is one difference. Unlike John, Simon is less intelligent than the average kid. On an intelligence test, Simon scored worse than 70% of the kids in his age group. Now let's think about the future earnings of Simon. Assuming that Simon is working full-time, what do you expect Simon's gross yearly earnings to be when he is 30 years old in each of the following scenarios:

A) If at age 5 the parents read to Simon every second day, they rarely take Simon to the playground and Simon watches TV for 2 hours every day, and at age 10 the parents show moderate interest in Simon's education, they don't talk to Simon very much, and they sometimes engage in activities together (e.g. go out for walks, have breakfast or tea together).

B) If at age 5 the parents read to Simon every day, they take Simon to the playground once every fortnight, and Simon watches TV for 1 hour every day, and at age 10 the parents show moderate interest in Simon's education, they don't talk to Simon very much, and they sometimes engage in activities together (e.g. go out for walks, have breakfast or tea together).

C) If at age 5 the parents read to Simon every day, they take Simon to the playground once every fortnight, and Simon watches TV for 1 hour every day, and at age 10 the parents show a lot of interest in Simon's education, they talk to Simon quite a lot, and they often *engage in activities together (e.g. go out for walks, have breakfast or tea together).*

D) If at age 5 the parents read to Simon every second day, they rarely take Simon to the playground and Simon watches TV for 2 hours every day, and at age 10 the parents show a lot of interest in Simon's education, they talk to Simon quite a lot, and they often engage in activities together (e.g. go out for walks, have breakfast or tea together).

D2. Parental Investment Questions

Investments at Age 5

1) How many hours a day does your child usually watch TV?

2) On how many days has your child been read to at home in the past 7 days?

3) In the past 7 days, has your child been to a park, recreation ground or adventure playground?

Investments at Age 10

1) As a family, how often do you do any of the following with your child? A) Go out for walks together, B) Have breakfast or tea together, C) Have a chat or talk with the child (for more than 5 min)

2) With regard to your child's education, how concerned or interested are you compared to other parents?

3) About how much time do you spend talking to your child each day?

Appendix E: Additional Tables and Figures

E1. Estimating the Investment Function Using the BCS

The investment function takes a 'reduced-form' as in equation (3). As mentioned earlier, there is no measure capturing parental beliefs about returns to investments in the BCS. Therefore, we have to drop α_6 from the estimation. All measures are normalized to have mean 0 and a standard deviation of 1 except for time investments at age 5.[34] The results are presented in Table E1. The first column shows the results for investments and determinants thereof as measured at age 5, while the second column refers to measures at age 10. The log-log form of the investment equation allows the interpretation of the parameter estimates as elasticities. For instance, a 1% increase in cognitive skills at age 5 increases investments by 0.455%.

We see that in both periods parents reinforce cognitive and noncognitive skills as investments are increasing in both stocks. However, at age 5 investments are more responsive to the stock of cognitive skills than noncognitive skills, whereas at age 10 the relation is reversed. Moreover, investments are increasing in both parental education and maternal noncognitive skills. Maternal noncognitive skills actually are a dominant driver of investments at age 10. Finally, boys receive lower investments, ceteris paribus, than girls as indicated by the statistically significant negative male dummy.

E2. Tables from BCS

[34]For time investments at age 5, we have the exact same information in the BCS as in our survey. Other measures are standardized in order to make the measures comparable across surveys.

Table E1—: Investment function for time (BCS)

Parameter	Age 5-9	Age 10-15
θ^C	.455	.154
SE	(.044)	(.036)
95% CI	[.369, .541]	[.083, .225]
θ^{NC}	.064	.164
SE	(.032)	(.116)
95% CI	[.001, .127]	[-.063, .391]
P^C	.314	.216
SE	(.031)	(.028)
95% CI	[.253, .375]	[.161, .271]
P^{NC}	.252	.54
SE	(.058)	(.058)
95% CI	[.138, .366]	[.426, .654]
Male	-.084	-.075
SE	(.032)	(.029)
95% CI	[-.147, -.021]	[-.132, -.018]
Shock	.234	.173
N	3,092	4,014

Datasource: BCS.
Notes: The table exhibits the results from estimating the investment function as in (3). Standard errors and 95% confidence intervals are obtained through bootstrapping.

Table E2—: Variance–covariance matrix of initial distribution (BCS)

	θ_0^C	θ_0^{NC}	P^C	P^{NC}
θ_0^C	.663	.147	.222	.127
θ_0^{NC}	.147	.518	.103	.24
P^C	.222	.103	.603	.185
P^{NC}	.127	.24	.185	.486

Datasource: BCS.
Note: Means are 0 for all variables.

Table E3—: Summary statistics of adulthood outcomes (BCS)

Outcome	Age	N	Mean	[SD]	Min	Max	Median
	21	431	9.7	[.54]	7.35	12.84	9.7
	26	2437	9.69	[.5]	5.72	11.39	9.74
Log income	30	2647	9.78	[.74]	2.91	15.17	9.89
	34	2202	10.21	[.88]	2.82	15.45	10.32
	38	1756	10.23	[.81]	6.05	14.66	10.32
	42	2255	10.14	[.95]	2.47	15.57	10.23
	21	339	9.8	[.49]	7.35	12.84	9.76
	26	2203	9.77	[.41]	5.72	11.39	9.77
Log income (full-time)	30	2250	9.93	[.62]	5.47	15.17	9.96
	34	1726	10.47	[.71]	2.82	15.45	10.47
	38	1320	10.5	[.61]	6.99	14.66	10.5
	42	554	10.34	[.68]	8.7	15.5	10.28
	21	236	2.08	[.57]	.4	5.94	2.06
	26	2413	2.08	[.4]	-2.03	4.51	2.08
Hourly log income	30	1014	2.16	[.65]	-2.65	6.82	2.15
	34	2195	2.69	[.69]	-5.38	7.62	2.7
	38	1747	2.76	[.62]	-.95	8.6	2.76
	42	947	2.58	[.74]	-4.19	7.81	2.56
	21	266	38.04	[8.43]	10	73	39
	26	2603	40.19	[10.43]	2	95	40
Hours worked	30	1035	35.06	[14.21]	1	99	37
	34	3143	29.1	[19.85]	0	99	37
	38	2187	36.57	[12.38]	1	80	38
	42	981	33.64	[12.67]	2	80	37
	21	552	.74	[.44]	0	1	1
	26	3095	.84	[.36]	0	1	1
Employment	30	3460	.85	[.36]	0	1	1
	34	3141	.85	[.35]	0	1	1
	38	2943	.86	[.34]	0	1	1
	42	3101	.73	[.45]	0	1	1
	21	480	.08	[.27]	0	1	0
	26	3095	.03	[.17]	0	1	0
Unemployment	30	3460	.02	[.15]	0	1	0
	34	3141	.01	[.11]	0	1	0
	38	2943	.02	[.13]	0	1	0
	42	3101	.03	[.17]	0	1	0
	26	3051	.29	[.45]	0	1	0
Married	34	3141	.56	[.5]	0	1	1
	38	2957	.62	[.49]	0	1	1
	26	3095	.2	[.4]	0	1	0
	30	3460	.21	[.41]	0	1	0
Smoking daily	34	3140	.18	[.38]	0	1	0
	38	2950	.14	[.35]	0	1	0
	42	3101	.14	[.34]	0	1	0
	21	531	7.38	[1.83]	0	10	8
	26	2785	7.83	[1.87]	0	10	7.78
Life satisfaction	34	3135	7.55	[1.69]	0	10	8
	42	3075	7.52	[1.85]	0	10	8
University	30	3454	.36	[.48]	0	1	0
Dropout	30	3454	.18	[.38]	0	1	0
Arrested	30	3434	.11	[.31]	0	1	0
Found guilty	30	3434	.08	[.27]	0	1	0
Voted	30	3451	.67	[.47]	0	1	1
Homeless	30	3200	.04	[.2]	0	1	0
Detained	30	3434	.09	[.28]	0	1	0
Wish not married	30	1511	.34	[.48]	0	1	0
Partner's log income	42	229	9.87	[1.05]	6.28	12.27	9.97

Datasource: BCS.

Table E4—: Production function of cognitive skills with interactions (BCS)

Interaction	With P^C x I		With θ^C,θ^{NC} x I		With θ^C x I		With θ^{NC} x I	
Parameter	Age 5-9	Age 10-15	Age 5-9	Age 10-15	Age 5-9	Age 10-15	Age 5-9	Age 10-15
θ^C	.644	.45	.55	.638	.615	.513	.581	.658
SE	(.037)	(.028)	(.022)	(.034)	(.025)	(.024)	(.025)	(.034)
95% CI	[.571, .717]	[.395, .505]	[.507, .593]	[.571, .705]	[.566, .664]	[.466, .560]	[.532, .63]	[.591, .725]
θ^{NC}	.078	.205	.08	.237	.088	.215	.085	.243
SE	(.026)	(.11)	(.015)	(.104)	(.017)	(.084)	(.017)	(.099)
95% CI	[.027, .129]	[-.011, .421]	[.051, .109]	[.033, .441]	[.055, .121]	[.05, .38]	[.052, .118]	[.049, .437]
I	.071	.207	.201	.245	.222	.218	.211	.254
SE	(.073)	(.066)	(.043)	(.063)	(.045)	(.05)	(.043)	(.058)
95% CI	[-.072, .214]	[.078, .336]	[.117, .285]	[.122, .368]	[.134, .31]	[.12, .316]	[.127, .295]	[.14, .368]
θ^C x I			.056	.084	.075	.053		
SE			(.087)	(.116)	(.096)	(.079)		
95% CI			[-.115, .227]	[-.143, .311]	[-.113, .263]	[-.102, .208]		
θ^{NC} x I			.112	-.203			.123	-.154
SE			(.073)	(.333)			(.079)	(.301)
95% CI			[-.031, .255]	[-.856, .45]			[-.032, .278]	[-.744, .436]
P^C	.27	.071						
SE	(.026)	(.026)						
95% CI	[.219, .321]	[.02, .122]						
I x P^C	-.063	.067						
SE	(.085)	(.136)						
95% CI	[-.23, .104]	[-.2, .334]						
Shock	.275	.075	.228	.082	.267	.081	.239	.089

Table E5—: Production function of noncognitive skills with interactions (BCS)

Interaction	With P^C x I		With θ^C,θ^{NC} x I		With θ^C x I		With θ^{NC} x I	
Parameter	Age 5-9	Age 10-15	Age 5-9	Age 10-15	Age 5-9	Age 10-15	Age 5-9	Age 10-15
θ^C	.138	.139	.235	.156	.226	.163	.249	.161
SE	(.037)	(.034)	(.028)	(.025)	(.026)	(.026)	(.03)	(.025)
95% CI	[.065, .211]	[.072, .206]	[.18, .29]	[.107, .205]	[.175, .277]	[.112, .214]	[.19, .308]	[.112, .21]
θ^{NC}	.49	.513	.525	.39	.503	.481	.555	.4
SE	(.027)	(.124)	(.022)	(.075)	(.02)	(.085)	(.024)	(.073)
95% CI	[.437, .543]	[.27, .756]	[.482, .568]	[.243, .537]	[.464, .542]	[.314, .648]	[.508, .602]	[.257, .543]
I	.142	.431	.227	.259	.219	.297	.24	.271
SE	(.073)	(.085)	(.057)	(.045)	(.052)	(.055)	(.061)	(.047)
95% CI	[-.001, .285]	[.264, .598]	[.115, .339]	[.171, .347]	[.117, .321]	[.189, .405]	[.12, .36]	[.179, .363]
θ^C x I			.058	.049	.052	.059		
SE			(.124)	(.099)	(.124)	(.092)		
95% CI			[-.185, .301]	[-.145, .243]	[-.191, .295]	[-.121, .239]		
θ^{NC} x I			-.045	.145			-.044	.169
SE			(.109)	(.274)			(.113)	(.259)
95% CI			[-.259, .169]	[-.392, .682]			[-.265, .177]	[-.339, .677]
P^C	.108	.081						
SE	(.027)	(.033)						
95% CI	[.055, .161]	[.016, .146]						
I x P^C	.121	-.164						
SE	(.095)	(.241)						
95% CI	[-.065, .307]	[-.636, .308]						
Shock	.159	.226	.156	.132	.197	.162	.159	.142

Table E6—: Coefficients of cognitive skills for adult outcomes (BCS)

		Log income					Hours	Satis-		Smoke
Age		Yearly	Hourly	Full-time	Emp.	Unemp.	worked	faction	Married	daily
21	Coef.	-.001	.083	.069	-.147	.043	-2.917	-.558	.	.
	SE	(.054)	(.063)	(.061)	(.044)	(.029)	(1.311)	(.221)	(.)	(.)
26	Coef.	.279	.245	.228	.06	.021	.543	.248	-.139	-.124
	SE	(.034)	(.031)	(.034)	(.016)	(.008)	(.443)	(.114)	(.019)	(.017)
30	Coef.	.393	.224	.278	.096	-.017	3.201	.	.	-.16
	SE	(.035)	(.05)	(.034)	(.014)	(.005)	(.822)	(.)	(.)	(.016)
34	Coef.	.606	.504	.435	.051	-.009	5.687	-.116	-.04	-.162
	SE	(.049)	(.038)	(.046)	(.013)	(.004)	(.768)	(.1)	(.023)	(.018)
38	Coef.	.51	.45	.454	.008	.012	1.736	.	-.014	-.114
	SE	(.051)	(.039)	(.051)	(.014)	(.005)	(.576)	(.)	(.023)	(.016)
42	Coef.	.502	.393	.444	.066	-.008	-1.3	.045	.	-.139
	SE	(.058)	(.065)	(.085)	(.017)	(.007)	(.901)	(.092)	(.)	(.016)

Datasource: BCS.
Notes: The table presents coefficients $\alpha_{1Q,l}$ of cognitive skills at different points of the life-cycle estimated as in equation (6), the function mapping skills at the end of childhood into outcomes over the lifecycle. Standard errors are obtained through bootstrapping.

Table E7—: Coefficients of noncognitive skills for adult outcomes (BCS)

		Log income					Hours	Satis-		Smoke
Age		Yearly	Hourly	Full-time	Emp.	Unemp.	worked	faction	Married	daily
21	Coef.	.169	-.013	.161	.152	-.171	4.121	1.912	.	.
	SE	(.115)	(.125)	(.115)	(.088)	(.053)	(2.107)	(.435)	(.)	(.)
26	Coef.	.495	.426	.449	.257	-.099	3.534	2.362	.16	-.219
	SE	(.058)	(.047)	(.05)	(.031)	(.016)	(.833)	(.208)	(.034)	(.033)
30	Coef.	.452	.394	.452	.137	-.039	3.697	.	.	-.192
	SE	(.063)	(.082)	(.061)	(.027)	(.011)	(1.449)	(.)	(.)	(.033)
34	Coef.	.738	.583	.651	.04	-.015	4.021	2.242	.423	-.211
	SE	(.105)	(.087)	(.103)	(.026)	(.009)	(1.425)	(.185)	(.042)	(.033)
38	Coef.	.623	.518	.639	.126	-.042	4.912	.	.396	-.211
	SE	(.099)	(.086)	(.112)	(.027)	(.01)	(1.036)	(.)	(.043)	(.031)
42	Coef.	.864	.572	.816	.059	-.033	5.596	1.829	.	-.199
	SE	(.111)	(.135)	(.142)	(.034)	(.013)	(1.501)	(.177)	(.)	(.031)

Datasource: BCS.
Notes: The table presents coefficients $\alpha_{2Q,l}$ of noncognitive skills at different points of the lifecycle estimated as in equation (6), the function mapping skills at the end of childhood into outcomes over the lifecycle. Standard errors are obtained through bootstrapping.

Table E8—: Coefficients of intercept for adult outcomes (BCS)

		Log income					Hours	Satis-		Smoke
Age		Yearly	Hourly	Full-time	Emp.	Unemp.	worked	faction	Married	daily
21	Coef.	9.616	2.028	9.721	.725	.065	36.983	7.489	.	.
	SE	(.026)	(.029)	(.027)	(.018)	(.01)	(.421)	(.089)	(.)	(.)
26	Coef.	9.467	1.952	9.589	.786	.023	36.825	7.662	.353	.238
	SE	(.015)	(.012)	(.013)	(.008)	(.003)	(.192)	(.051)	(.009)	(.008)
30	Coef.	9.496	2.051	9.75	.766	.023	30.492	.	.	.243
	SE	(.018)	(.02)	(.017)	(.007)	(.002)	(.329)	(.)	(.)	(.007)
34	Coef.	9.775	2.449	10.189	.781	.011	22.914	7.48	.557	.222
	SE	(.023)	(.018)	(.025)	(.007)	(.002)	(.299)	(.046)	(.01)	(.008)
38	Coef.	9.802	2.517	10.178	.8	.013	30.725	.	.605	.165
	SE	(.023)	(.018)	(.025)	(.007)	(.002)	(.254)	(.)	(.01)	(.007)
42	Coef.	9.708	2.355	10.023	.707	.043	28.924	7.468	.	.164
	SE	(.026)	(.03)	(.032)	(.008)	(.003)	(.358)	(.041)	(.)	(.007)

Datasource: BCS.
Notes: The table presents intercepts $\alpha_{Q,l}$ at different points of the lifecycle estimated as in equation (6), the function mapping skills at the end of childhood into outcomes over the lifecycle. Standard errors are obtained through bootstrapping.

Table E9—: Coefficients of male dummy for adult outcomes (BCS)

		Log income					Hours	Satis-		Smoke
Age		Yearly	Hourly	Full-time	Emp.	Unemp.	worked	faction	Married	daily
21	Coef.	.192	.135	.153	.063	.039	3.215	-.326	.	.
	SE	(.037)	(.042)	(.036)	(.026)	(.018)	(.765)	(.137)	(.)	(.)
26	Coef.	.325	.124	.227	.077	.026	7.483	-.078	-.139	.002
	SE	(.018)	(.015)	(.016)	(.01)	(.005)	(.261)	(.066)	(.011)	(.011)
30	Coef.	.433	.181	.202	.139	.014	12.041	.	.	.003
	SE	(.021)	(.029)	(.022)	(.007)	(.003)	(.477)	(.)	(.)	(.01)
34	Coef.	.656	.275	.288	.158	.008	12.553	-.091	-.034	-.006
	SE	(.028)	(.023)	(.028)	(.007)	(.003)	(.446)	(.056)	(.014)	(.01)
38	Coef.	.709	.3	.354	.135	.007	12.602	.	-.014	.025
	SE	(.029)	(.025)	(.032)	(.008)	(.003)	(.322)	(.)	(.013)	(.01)
42	Coef.	.709	.401	.374	.015	-.021	13.142	-.156	.	.016
	SE	(.035)	(.044)	(.052)	(.01)	(.004)	(.521)	(.051)	(.)	(.009)

Datasource: BCS.
Notes: The table presents coefficients $\alpha_{3Q,l}$ of the male dummy at different points of the lifecycle estimated as in equation (6), the function mapping skills at the end of childhood into outcomes over the lifecycle. Standard errors are obtained through bootstrapping.

E3. Decomposing the Survey Sample By Period

In Table E10 we equalize inputs in only one of the two periods to get an idea of the relative contribution to the heterogeneity in outcomes. Differences in early and late beliefs can account for 2% and 1% of the variance in discounted lifetime income, respectively. Therefore, the relative contribution of beliefs to the variance in outcomes is greater at the earlier stage. For investments, we generally observe the opposite. Equalizing investments at the early stage reduces the variance in discounted lifetime earnings by 9% compared to 30% when equalizing late investments. Therefore, the heterogeneity in late investments contributes more to the variation in outcomes than the heterogeneity in early investments does.

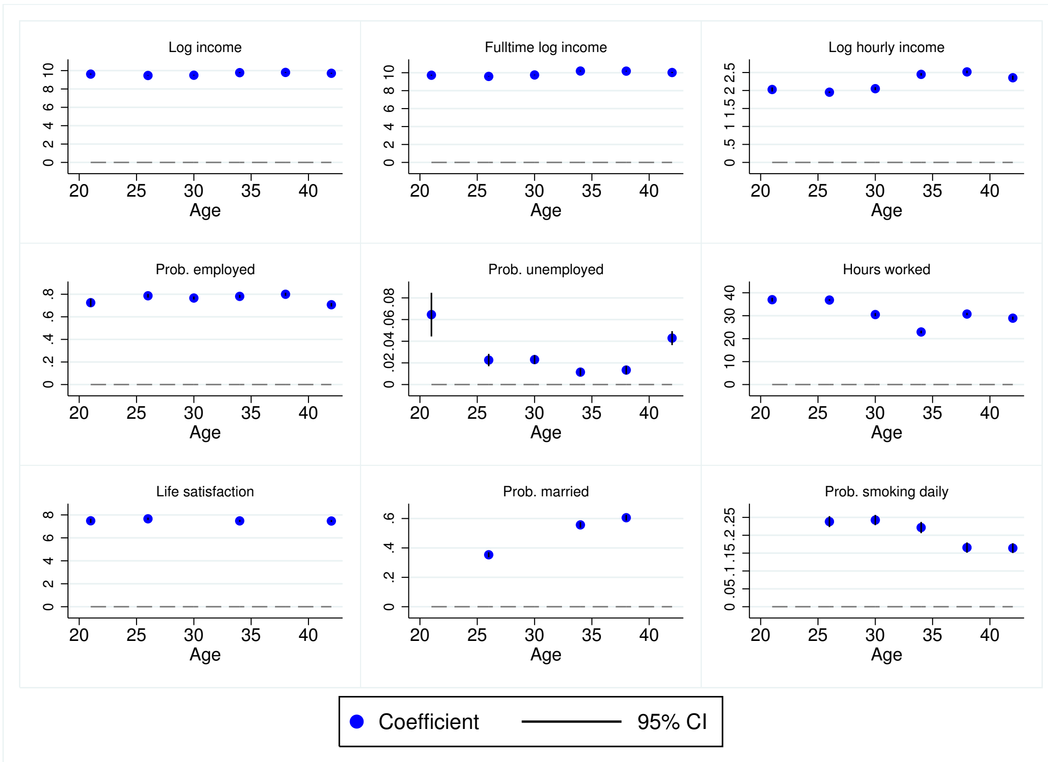
Table E10—: Variance in outcomes explained by inputs by period

Outcome	Mean	Var.	t	ϕ	I	P^C	P^{NC}	P
Skills								
$\ln \theta_T^C$	.03	.34	0	.34	.32	.34	.34	.34
				(.01)	(.07)	(.00)	(.02)	(.02)
			1	.34	.28	.34	.33	.33
				(.01)	(.17)	(.00)	(.03)	(.03)
$\ln \theta_T^{NC}$	.04	.38	0	.38	.37	.38	.38	.38
				(.01)	(.05)	(.00)	(.01)	(.01)
			1	.38	.3	.38	.37	.37
				(.01)	(.21)	(.00)	(.03)	(.03)
Income								
Discounted lifetime	245,820	4.82	0	4.74	4.41	4.81	4.71	4.71
				(.02)	(.09)	(.00)	(.02)	(.02)
			1	4.77	3.37	4.81	4.57	4.56
				(.01)	(.30)	(.00)	(.05)	(.05)
Disc. life. (full-time)	275,655	4.37	0	4.31	4.01	4.37	4.28	4.28
				(.01)	(.08)	(.00)	(.02)	(.02)
			1	4.33	3.13	4.36	4.16	4.16
				(.01)	(.28)	(.00)	(.05)	(.05)
Labor market								
Hours worked	33.36	42.55	0	42.42	42.19	42.55	42.37	42.37
				(.00)	(.01)	(.00)	(.00)	(.00)
			1	42.47	39.73	42.55	42.11	42.1
				(.00)	(.07)	(.00)	(.01)	(.01)
Education								
University	.35	.11	0	.11	.1	.11	.11	.11
				(.01)	(.04)	(.00)	(.01)	(.01)
			1	.11	.09	.11	.11	.11
				(.01)	(.14)	(.00)	(.02)	(.02)
Dropout	.26	.05	0	.05	.05	.05	.05	.05
				(.01)	(.06)	(.00)	(.01)	(.01)
			1	.05	.04	.05	.05	.05
				(.01)	(.19)	(.00)	(.03)	(.03)

Datasource: BCS.
Notes: The columns refer to the input that is equalized in the experiment. For each outcome the top row exhibits the sample variance, and the bottom row in brackets represents the fraction by which the variance has been reduced by equalizing the respective input. Discounted lifetime income is computed from age 26 to 42 by interpolating linearly between available data points and discounted using a 2% annual interest rate. Estimated income at a given age is multiplied with the estimated probability of employment. For discounted lifetime income all variances have to multiplied by 10^{10}.

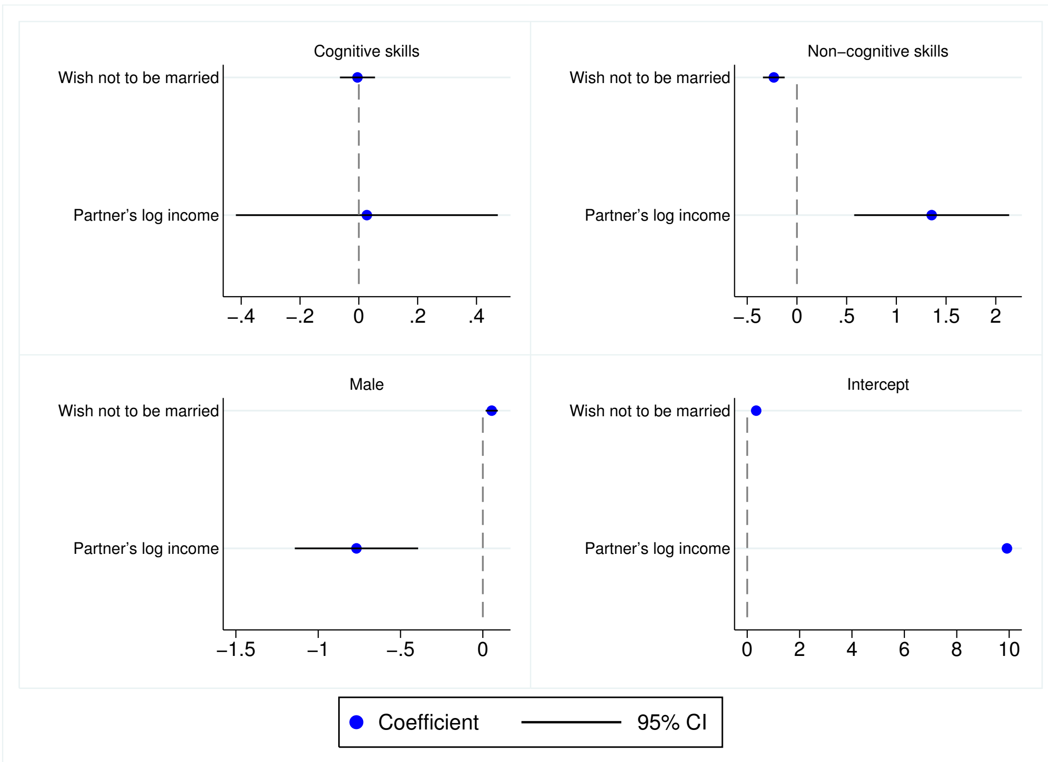
E4. Figures from BCS

Figure E.1. : Intercept over the lifecycle



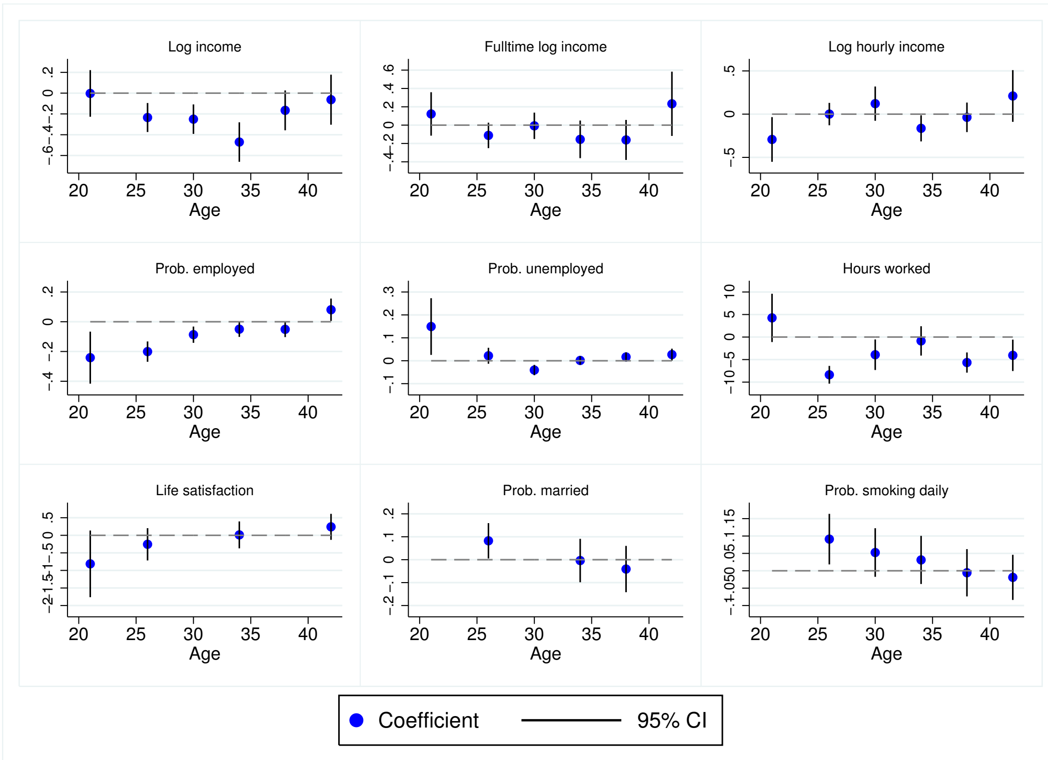
Datasource: BCS.
Note: The figure displays intercepts $\alpha_{Q,l}$ at different points of the lifecycle with 95% confidence intervals estimated as in equation (6), the function mapping skills at the end of childhood into outcomes over the lifecycle. The titles indicate the outcome while the x-axis specifies the age at which the outcome is measured.

Figure E.2. : Determinants of adult outcomes at age 42



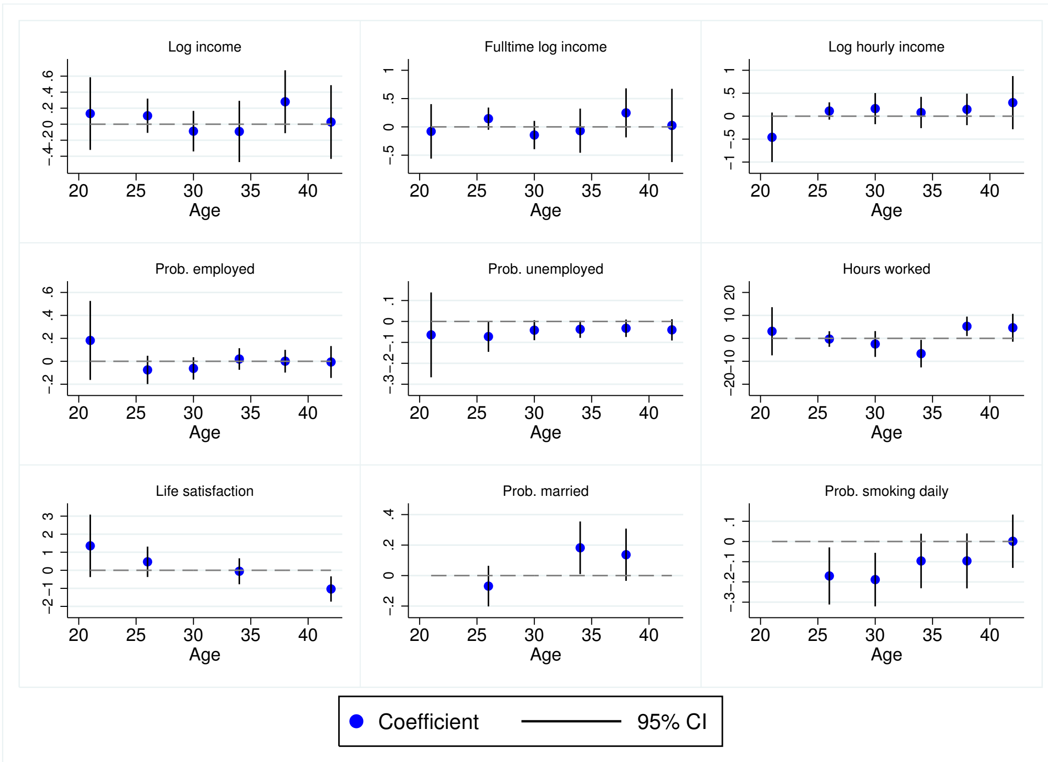
Datasource: BCS.
Note: The figure displays coefficients $\alpha_{Q,l}$ with 95% confidence intervals estimated as in equation (6), the function mapping skills at the end of childhood into outcomes at age 42. The titles indicate the independent while the y-axis specifies the dependent variables.

Figure E.3. : Effects of cognitive skills interacted with male dummy over the lifecycle



Datasource: BCS.
Note: The figure displays coefficients of the interaction term of cognitive skills with the male dummy added to equation (6) for adult outcomes with 95% confidence intervals. The titles indicate the outcome while the x-axis specifies the age at which the outcome is measured.

Figure E.4. : Effects of noncognitive skills interacted with male dummy over the lifecycle



Datasource: BCS.
Note: The figure displays coefficients of the interaction term of noncognitive skills with the male dummy added to equation (6) for adult outcomes with 95% confidence intervals. The titles indicate the outcome while the x-axis specifies the age at which the outcome is measured.

E5. Tables from survey

Table E11—: Summary of children's skills (survey)

	Age 3-9		Age 10-18	
	Mean	[SD]	Mean	[SD]
Cognitive skills				
Math	76.04	[19.74]]	80.08	[17.22]
Reading	69.26	[21.16]	80.42	[18.55]
School performance	72.4	[19.97]	81.44	[17.26]
Noncognitive skills				
Restless	40.99	[30.36]	26.41	[27.18]
Distressed	12.43	[15.96]	12.62	[17.97]
Disobedient	22.22	[21.34]	14.49	[19.26]
Observations	224		1,452	

Datasource: Own survey.
Note: Parents were asked to score children on a scale from 0-100 where 100 is the best possible score.

Table E12—: Summary of parental noncognitive skills (survey)

	Strongly disagree	Disagree	Neither nor	Agree	Strongly agree
Easily upset	.19	.3	.22	.26	.03
Feel rushed	.45	.24	.18	.11	.02
Depressed	.43	.25	.1	.16	.06

Datasource: Own survey.

Table E13—: Variance–covariance matrix of initial distribution from survey

	θ_0^C	θ_0^{NC}	P^C	P^{NC}	ϕ_0	ϕ_1	y_0
θ_0^C	.385	.007	.007	.166	.018	.003	.087
θ_0^{NC}	.007	.267	-.009	.018	.002	.003	.345
P^C	.007	-.009	1.098	-.009	.011	.054	.334
P^{NC}	.166	.018	-.009	.283	.011	-.004	.079
ϕ_0	.018	.002	.011	.011	.015	.055	.054
ϕ_1	.003	.003	.054	-.004	.055	.047	-.017
y_0	.087	.345	.334	.079	.054	-.017	.433
Mean	0	0	0	0	.093	.305	10.979

Datasource: Own survey.
Note: y_0 stands for log household income at age 5.

Weighting survey

In order to account for the fact that our sample is biased towards households with higher income, we weight households by household income in order to resemble the distribution of households in the FRS 2013-2014. In Table E14, we present estimates for the investment function including weights. While in the benchmark case investments react with a .51% and .37% increase to a one-percentage point increase in early and late beliefs, respectively, in the weighted sample the response is .65% and .33%. Hence, investments respond more strongly to early beliefs and less to late beliefs in the weighted sample than in the benchmark case. However, given that the differences are not large in magnitude, we are confident in using the unweighted sample as a benchmark.

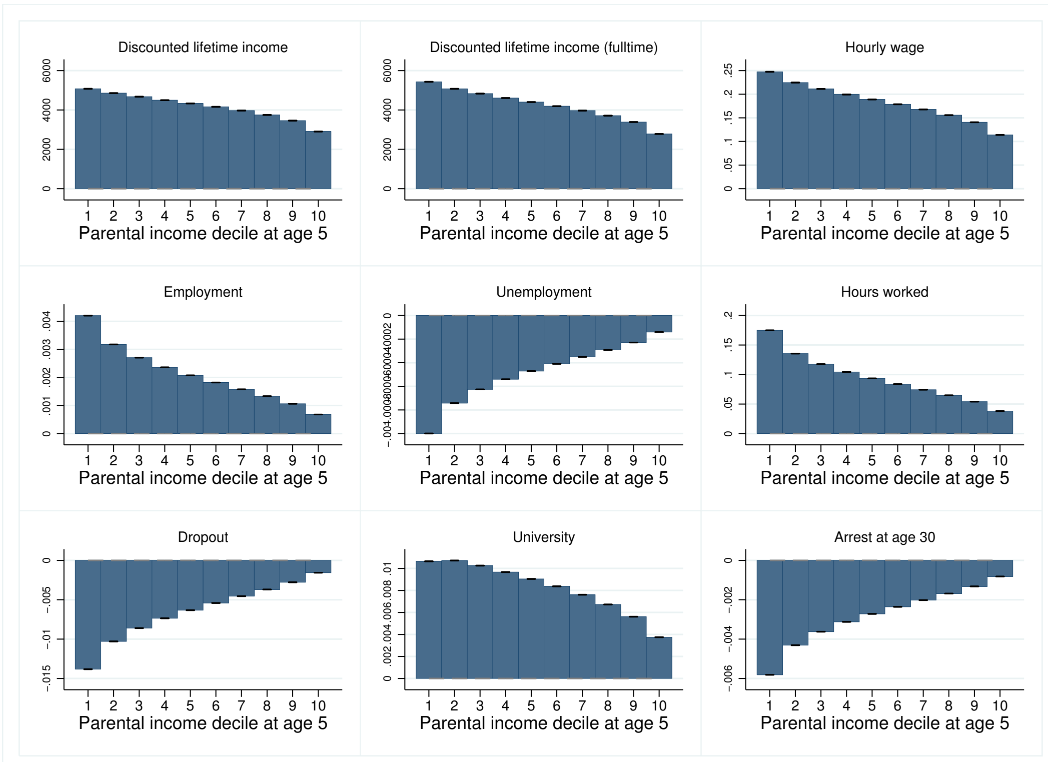
Table E14—: Investment function for time (survey with weights)

Parameter	Age 5-9	Age 10-15
θ^C	.054	.086
SE	(.055)	(.033)
95% CI	[-.054, .162]	[.021, .151]
θ^{NC}	.198	.278
SE	(.059)	(.046)
95% CI	[.082, .314]	[.188, .368]
P^C	.035	.009
SE	(.026)	(.018)
95% CI	[-.016, .086]	[-.026, .044]
P^{NC}	.178	.27
SE	(.074)	(.04)
95% CI	[.033, .323]	[.192, .348]
Male	-.116	.028
SE	(.053)	(.038)
95% CI	[-.22, -.012]	[-.046, .102]
ϕ	.652	.329
SE	(.176)	(.077)
95% CI belief	[.307, .997]	[.178, .48]
Shock	.025	.247
N	224	1,454

Datasource: Own survey.
Notes: Standard errors and 95% confidence intervals are obtained through bootstrapping. ϕ represents beliefs about returns. Survey weights are computed in order to match a representative distribution in terms of household income using the FRS 2013-2014.

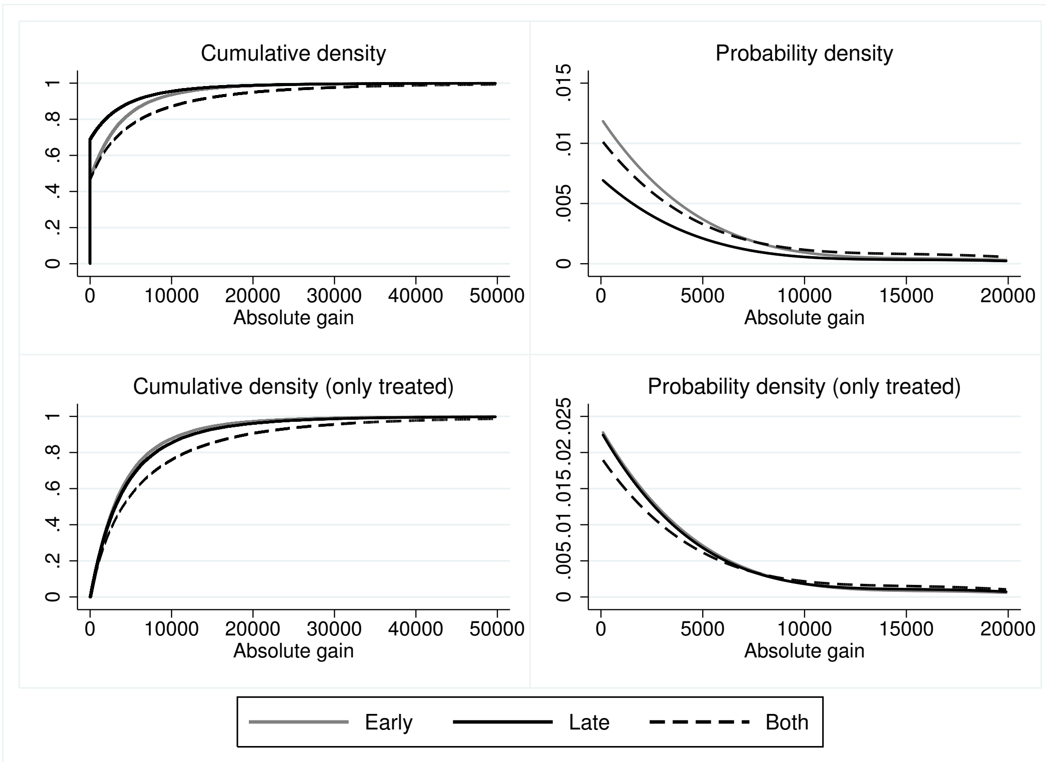
E6. Figures from counterfactuals in survey

Figure E.5. : Absolute gain by parental income decile at age 5



Note: Note: The figure depicts the average absolute gain by parental income decile at age 5 of the belief treatment for a range of outcomes. The treatment involves increasing beliefs of parents with perceived returns lower than 'true' returns to the 'true' level. 95% confidence intervals of the mean effect by decile are computed from 1,000 simulations.

Figure E.6. : Distribution of treatment effect of shift in beliefs on discounted lifetime income



Note: In this simulation we increase beliefs for parents with perceived returns lower than 'true' returns to the 'true' level. The gray solid line is for ϕ_0, the black solid for ϕ_1, and the dashed line when increasing both. In the top panels the cumulative (left) and probability (right) density is presented for the entire population. In the bottom two panels we have the same information conditional on having a positive gain.