# Socio-Economic Status and Inequalities in Children's IQ and Economic Preferences*

Armin Falk[1,2], Fabian Kosse[1,2],
Pia Pinger[1,2], Hannah Schildberg-Hörisch[3], Thomas Deckers[1]

[1] University of Bonn, Institute for Applied Microeconomics
[2] Behavior and Inequality Research Institute (briq)
[3] University of Düsseldorf, Düsseldorf Institute for Competition Economics (DICE)

March 2019

**Abstract**

This paper explores inequalities in IQ and economic preferences between children from high and low socio-economic status (SES) families. We document that children from high SES families are more intelligent, patient and altruistic, as well as less risk-seeking. To understand the underlying causes and mechanisms, we propose a framework of how parental investments as well as maternal IQ and economic preferences influence a child's IQ and preferences. Within this framework, we allow SES to influence both the level of parental time and parenting style investments, as well as the productivity of the investment process. Our results indicate that disparities in the level of parental investments hold substantial importance for SES gaps in economic preferences and, to a lesser extent, IQ. In light of the importance of IQ and preferences for behaviors and outcomes, our findings offer an explanation for social immobility.

*Keywords*: socio-economic status, time preferences, risk preferences, altruism, experiments with children, origins of preferences, human capital

*JEL-Codes*: C90, D64, D90, D81, J13, J24, J62

*Corresponding author: armin.falk@uni-bonn.de. Armin Falk gratefully acknowledges financial support through the Leibniz Programme of the German Science Foundation (DFG) and the Benckiser Stiftung Zukunft.

# 1 Introduction

Both economic theory and empirical evidence have established a robust link between IQ and economic preferences and many important outcomes in life. More intelligent individuals achieve higher levels of education, income, occupational status, job performance and better health outcomes (Heckman and Vytlacil, 2001; Schmidt and Hunter, 2004; Strenze, 2007; Hanushek and Woessmann, 2008; Almlund et al., 2011). Similarly, more patient individuals are less likely to be involved in crime (Åkerlund et al., 2016), have higher educational attainment, occupational success, income and wealth (Ventura, 2003; Eckel, Johnson, and Montmarquette, 2005; DellaVigna and Paserman, 2005; Golsteyn, Grönqvist, and Lindahl, 2014; Cadena and Keys, 2015; Dohmen et al., 2018) and better health outcomes (Fuchs, 1982; Kirby, Petry, and Bickel, 1999; Bickel, Odum, and Madden, 1999; Kirby and Petry, 2004; Chabris et al., 2008; Golsteyn, Grönqvist, and Lindahl, 2014; Cadena and Keys, 2015). Risk preferences predict labor market and health outcomes, investing and addictive behaviors, as well as migration decisions (Barsky et al., 1997; Hong, Kubik, and Stein, 2004; Bonin et al., 2007; Anderson and Mellor, 2008; Kimball, Sahm, and Shapiro, 2008; Jaeger et al., 2010; Dohmen et al., 2011; Dohmen and Falk, 2011; von Gaudecker, van Soest, and Wengström, 2011; Becker et al., 2012; Dawson and Henley, 2015; Hsieh, Parker, and van Praag, 2017). Finally, social preferences are associated with cooperative behavior in various domains of life, including the work place, donating, repayment of loans or management of common pool resources (Karlan, 2005; Dohmen et al., 2009; Rustagi, Engel, and Kosfeld, 2010; Carpenter and Seki, 2011; Becker et al., 2012; Burks et al., 2016; Deming, 2017). Table A1 in the appendix provides a comprehensive summary of the empirical evidence.[1]

IQ and preferences are not only associated with key outcomes in adulthood, but also in childhood and adolescence. In particular, higher IQ is positively associated with success in school (Reynolds, Temple, and Ou, 2010; Almlund et al., 2011) and impatience is linked to drinking and smoking, a higher body mass index, a lower propensity to save and worse education outcomes (Castillo et al., 2011; Sutter et al., 2013; Castillo, Jordan, and Petrie, 2015). Like adults, more risk-taking children and adolescents are more likely to be overweight or obese (Sutter et al., 2013). Importantly, these associations tend to persist, as measures of IQ and economic preferences in childhood or adolescence have also been shown to predict adult outcomes (Strenze, 2007; Borghans, ter Weel, and Weinberg, 2008; Golsteyn, Grönqvist, and Lindahl, 2014).[2]

[1] For more extensive evidence on IQ and outcomes, we refer the reader to several meta-analyses and overview articles (Schmidt and Hunter, 2004; Strenze, 2007; Almlund et al., 2011).

[2] Related literature in psychology on childhood temperament documents (i) that childhood temperament predicts functioning in childhood, (ii) the existence of some continuity in IQ and temperament development

Differences in preferences also determine outcomes at the societal level. For instance, aggregate patience relates to the level of economic development of countries and regions, risk preferences predict labor protection policies and social preferences are associated with the frequency of armed conflicts (Hübner and Vannoorenberghe, 2015; Dohmen et al., 2018; Falk et al., 2018). The relevance of IQ and preferences at the individual and aggregate level calls for a better understanding of their origins. In particular, if systematic differences in IQ and preferences emerge during childhood and are linked to the family environment, this may provide further evidence for inequality being founded early in life, with important implications for persistence of inequality and social immobility.

This paper contributes to the understanding of the origins of inequality by documenting a systematic and strong relation between a family's socio-economic status (SES) and a child's economic preferences and IQ. Establishing such a relationship is challenging, as it requires comprehensive information concerning a household's socio-economic environment, as well as precise measures of the offspring's preferences and IQ. We have collected such data for 435 parents and their children. They contain parent surveys on the household environment, including detailed measures of SES, maternal preferences and IQ, parenting styles and time investments. They also comprise results from high-quality IQ tests and incentivized, experimentally-elicited measures of patience, risk-taking and altruism for the children. All measurements were elicited twice under identical conditions, but with several months in between. Moreover, SES was part of the sampling scheme, such that families can be naturally classified into high and low SES families, depending on the level of parental education and household income. In presenting our results, we first use this classification to document early gaps in the children's IQ and preferences. Subsequently, in line with some of the recent literature (Cunha and Heckman, 2007; Cobb-Clark, Salamanca, and Zhu, 2016; Doepke and Zilibotti, 2017), we propose and estimate a framework in which SES can influence both the level of investments and their overall productivity.

Our main finding is that gaps in time, risk and social preferences as well as IQ open up early in life and are strongly related to a child's socio-economic environment. Children from families with higher SES are significantly more patient and altruistic, less likely to be risk-seeking and they score higher on IQ tests. The SES gaps are sizable. They amount to around 0.65 of a standard deviation in IQ and range between 0.21 and 0.35 of a standard deviation in preferences by mid-elementary school age. These gaps compare to about half of the black-white achievement gaps in the US and are larger than the estimated effects of most

from early childhood to early adulthood and (iii) that early childhood differences in temperament are systematically related to a broad range of adult outcomes (Caspi, 2000; Caspi et al., 2003; Moffitt et al., 2011).

intervention programs. The overall pattern of results suggests that childhood circumstances cumulate as low parental education and low parental income tend to reinforce each other if both are present in a single family. Our findings indicate that the SES gaps are mostly driven by differences in maternal characteristics and by SES-related disparities in the level of parental investments, while SES-related differences in the productivity of the investment process are largely irrelevant.

We move beyond existing work in at least three respects. First, this is the only paper to date that consistently relates precise measures of socio-economic disparities in the household environment to key economic preferences in children.[3] The reason is a prior lack of data combining incentivized measures of children's economic preferences with detailed information on their family environment.[4] Given the considerable importance of preferences in economic theory and empirical work, the literature on the relationship between a child's economic preferences and its household environment is surprisingly scarce. For time preferences, the study by Delaney and Doyle (2012) comes closest to analyzing this relationship. They use parental answers to questions concerning psychological concepts such as hyperactivity, impulsivity and persistence of three year-old children and show that children from families with higher SES are less impulsive. Concerning risk preferences, Alan et al. (2017) study the intergenerational transmission of risk attitudes, using maternal and paternal years of education as control variables. Regarding social preferences, Bauer, Chytilová, and Pertold-Gebicka (2014) is the only closely-related study.[5] Similar to us, they find a positive relationship between parental education and altruism in primary school children.[6]

Second, what sets our paper apart from existing studies is that we study time preferences, risk preferences, social preferences and IQ in the same sample of children and in one coherent framework. This is important, as no economic decision involves only one preference or cognitive aspect. For example, addictive behaviors such as smoking, drinking or gambling involve risk considerations, but also a trade-off between immediate and delayed

[3]While research on the relation between SES and children's economic preferences remains in its infancy, the effect of SES on children's overall IQ is well established (see Bradley and Corwyn, 2002, for a summary of the literature).

[4]For a discussion see also Falk and Kosse (2016), who use breastfeeding duration as a proxy to explore the relation between early-life circumstance and preferences.

[5]Benenson, Pascoe, and Radmore (2007) also present evidence that higher SES is associated with higher levels of altruism. However, in their study, SES is only measured at the school level, using the fraction of children who receive a free lunch. Angerer et al. (2015a) use children's statements about their parents' profession to deduce measures of parental income and education. They find a marginally significant, positive effect of higher paternal education on children's donations to a charity.

[6]In addition, psychological literature exists focusing on the relation of more broadly-defined concepts, such as socio-emotional behavior, cognitive development and family adversity (see, e.g., Obradović et al., 2010; Burchinal et al., 2000, and the references therein). This work follows a different tradition and the measures are usually not incentivized.

utility (Ida and Goto, 2009; Sutter et al., 2013). In this respect, our approach offers a more holistic view of SES-related disparities in child characteristics that matter for economic decision-making.

Third, above and beyond studying SES as a "black box", we provide a simple, static framework to study how the family environment differs by SES and why these differences translate into differences in children's time preferences, risk preferences, altruism and IQ. Within this framework, we capture several aspects of developmental inputs, such as parenting style investments, parental time investments and the IQ and preferences of the child's mother. We allow SES to affect both the *level* of parental investments and the *productivity* of the investment process. In addition to a direct intergenerational transmission of IQ and economic preferences from mothers to children, we find that socio-economic differences in child IQ and preferences are mostly due to differences in parental inputs, i.e., the parenting style and time investments, and not due to differences in productivity. Our model estimates can be used to study the extent to which the SES gap in IQ and economic preferences would be reduced in the presence of policies that target economic resources or parental investments, respectively.

The remainder of the paper is organized as follows. First, we describe the composition of our sample, the data collection process, our definition of SES and our measures of economic preferences and IQ. Section 3 provides descriptive evidence on gaps in IQ and preferences between children from high and low SES households. Section 4 presents and estimates a framework of how maternal IQ and preferences, household income, parental education and investments interact to form a child's preferences and IQ. In the final section, we discuss the implications of our findings and conclude.

# 2 Data

This section introduces the data and describes our measures of IQ and preferences. We first report how the families were recruited and interviewed, as well as how we classified them in terms of SES. We then provide a detailed description of the incentivized experiments and IQ tests.

## 2.1 Sampling and data collection

Our sample comprises 435 children and their mothers.[7] The families were recruited using official registry data comprising more than 95% of the addresses of families living in Bonn and Cologne (Germany) who had children aged 7-9. Offers to take part in the study were sent by mail to all families with children born between September 2003 and August 2004 and one-third of families with children born between September 2002 and August 2003. 12.5% (N=1874) of the contacted families agreed to participate.[8] Since our main focus is on SES-related disparities in child IQ and preferences, we distinguished between two groups of families. First, we invited all low-income, low parental education or single parent families to obtain a large sample of socio-economically disadvantaged children. A family was categorized as "low income" if its household equivalence income was lower than the 30th percentile of the German income distribution, and as "low education" if neither parent has obtained a university entrance certificate. Second, we invited a randomly-chosen subgroup of 150 families who did not meet any of the above criteria.

All 435 children and their mothers took part in two consecutive interviews, with a time interval of 16 months.[9] These interviews took place in their respective hometown in centrally-located apartments that where rented and equipped for the purpose of this study. The data collections were conducted by trained university students (mostly graduates) of psychology or education science and lasted about one hour.[10] During the interviews and experiments, the interviewer, the mother and the child were in the same room. However, a standardized seating plan ensured that the mother and child did not have eye contact and could not communicate otherwise.

During the interviews, the children participated in a sequence of seven experiments, two intelligence tests (one on fluid and one on crystallized IQ) and answered a brief questionnaire. While the children participated in the experiments, their mothers filled out

[7]During the interviews, 96% of the children were accompanied by their biological mother, 2% by their biological father, 3 children by a step or foster parent and one child by the new partner of a biological parent. We do not have unambiguous information on the accompanying person for about 1% of the children. Throughout the paper, we will use the term "mother" for the adult accompanying the child.

[8]The parents answered a short screening questionnaire about the socio-economic characteristics of the household, consented to let their children participate in the study and (if selected) to let them take part in a one-year mentoring program. In our analysis, we exclude the subgroup of selected children. An additional requirement was that the families speak (at least some) German at home, to ensure that both the children and their mothers understood the questionnaire items and experimental instructions, which were phrased in German.

[9]At the time of the first data collection, the children were on average 7.8 years old. At the time of the second data collection, the children were on average 9.1 years old.

[10]All mothers received a flat payment of 35 Euros in the first data collection and 45 Euros in the second data collection to cover travel expenses and incentivize participation.

a comprehensive questionnaire. First, they provided general information about the child, such as name, age, gender and the number of older and younger siblings. Second, they answered a battery of questions related to the socio-economic background of the family. Third, they were asked to provide information on the childhood environment, including measures of parenting style, parent-child activities, an assessment of how satisfied the parents were with their child's development, as well as some information about the children's fathers. Finally, the mother answered a battery of questions regarding her own economic preferences and completed an IQ test. Maternal economic preferences were elicited using the questionnaire measures validated by Falk et al. (2016) and maternal IQ was measured by a short version of the Standard Progressive Matrices Plus test (SPM Plus).[11]

Families in this study are not necessarily representative of the German population. All families live in the same part of the country, study participation was voluntary and SES was part of the sampling scheme. In particular, they may differ systematically in terms of maternal intelligence and maternal economic preferences. To investigate non-random selection, we compare our sample along several dimensions to the German Socio-Economic Panel (SOEP), a representative sample of households in Germany. Note that a substantial part of the questionnaire answered by the mothers matched the SOEP questionnaire. When compared to the SOEP, our sample indeed comprises a moderately higher share of high SES households, as well as more intelligent, altruistic and risk-taking mothers (see table B1).

We are interested in assessing effect sizes that are interpretable in terms of population standard deviations. Thus, we proceed as follows. First, we construct inverse probability weights (IPWs) that account for systematic differences in SES, maternal IQ, and maternal preferences between our sample and the representative SOEP data (for details, see Section B.1.1). We then use these weights, to estimate the moments of the population distribution. Last, we standardize our measures of child IQ and economic preferences using these moments. In addition, we draw on the aforementioned weights to evaluate the robustness of our results with respect to self-selection. Moreover, we construct a second set of weights, which allows us to assess and correct for potential non-random attrition (attrition is 16.2%, see Section B.1.2 for a description of the weighting scheme).

## 2.2 Socio-economic status

Common classifications of SES rely on income or education (see, e.g., Ganzeboom, De Graaf, and Treiman (1992)). In line with this literature and our initial sampling scheme, we clas-

[11] For a detailed description of the maternal preference and IQ measures, see Section B.2.

sify a family as "low SES" if either one or both of the following conditions are met: (i) the parents are low-educated, i.e., neither parent has obtained a university entrance certificate; or (ii) net equivalence household income lies below the 30th percentile of the German income distribution.[12] All other families are classified as "high SES".

Later, we also use parental education and household income as continuous measures of a child's socio-economic background. For education, we construct a measure comprising the overall number of years of education averaged over mothers and fathers, i.e., including vocational training and university education. For income, we use net monthly household equivalence income, computed in line with standard OECD and EUROSTAT procedures (see Hagenaars, De Vos, and Zaidi, 1994).[13] Our income measure thus accounts for both the number of individuals living in a household and economies of scale that arise as the household size increases.

Education is a measure of human capital and thus a primary means to generate income. As a result, our data display a strong correlation ($\rho = 0.57$) between parental education and family income. 45% of the children with low-educated parents experience both low parental education and low family income as two forms of socio-economic disadvantage.

## 2.3 Description of experiments and IQ tests

In the following, we explain the experiments to measure patience, risk-taking and altruism in children, before we present the IQ tests. To assess preferences, we relied on a combination of established and newly-developed measurement tools, which were carefully pre-tested and adapted to the children's age range. All experiments were incentivized using toys and a small amount of money. For this purpose, we introduced an experimental currency called "stars". After the interview, children could exchange the number of paper stars that they had collected in the experiments for toys (see the picture in figure A1). A reward with the monetary equivalent of 4 Euro was guaranteed. Each star collected in the experiments increased the value of the reward by 0.15 Euro. For comparison, note that the mean amount of pocket money in our sample was about 1.5 Euro per week. In order to minimize "in-experiment wealth effects", all earned stars were put in separate paper bags after each experiment, such that the children could not see their accumulated "wealth". We used

[12]The monthly net household equivalence income threshold of 1,065 Euro is calculated based on representative household data (SOEP, 2010). It closely aligns with the official poverty line (e.g., 1,033 Euro in 2015).

[13]Net monthly household equivalence income is computed by dividing total monthly nominal household income (after taxes, but including all transfers) by a factor that takes the household's size and composition into account. The factor takes on the value 1 for a single-person household. For each additional person aged 14 years or older 0.5 is added, while for each person younger than 14 years 0.3 is added.

standardized control questions to verify that all participating children had understood the instructions.[14]

At both data collections, the interviews, experimental procedures and tests were identical and administered in the same fixed order. For each child and variable we thus obtain two measures, which we aggregate using equal weights. Hence, our measures are an assessment of the child's economic preferences in mid-childhood, which is considered as a single development stage in much of developmental psychology (e.g., Inhelder and Piaget, 1958; Berger, 2011).[15] This procedure reduces random measurement error, which tends to be larger in measures of economic preferences, based on a single experiment, than is the case, e.g., for multi-item survey measures of personality traits, for details see Section B.3.[16] Experimentally-elicited preference measures bear several important advantages: they are constructed from revealed preferences in well-defined and controlled contexts. This gives them a readily-interpretable metric, likely reduces non-random measurement error and allows for a straightforward comparison across individuals.

### 2.3.1 Time preferences: piggy bank experiment

Our measure of patience is the number of saved coins in a piggy bank. We developed the piggy bank experiment as an age-adapted version of the common time preference elicitation paradigm for adults, which involves trade-offs between smaller but sooner available amounts of money and larger but delayed amounts of money. Children were endowed with seven 20 cent coins. They could choose how many coins to put in a piggy bank and how many to take immediately. The amount put in the piggy bank was doubled and sent to the children via postal mail one week after the interview. To ensure that the children were certain to receive the money, we explicitly addressed the letter to the children themselves, wrote the address on the envelope and put the saved amount of money in the envelope while the children were watching. We also handed out contact details for questions or requests.

---

[14] Less than 1% of the observations had to be excluded because the children did not fully understand the experimental protocol.

[15] All results remain qualitatively the same when we conduct our analyses separately for each of the two data collections.

[16] For economic preferences, test-retest correlations are in the range of 0.1-0.5 (see Chuang and Schechter, 2015), while for personality traits they are as high as 0.6-0.8 (see Roberts and DelVecchio, 2000). We analyze and discuss the test-retest properties of our measures in Section B.3. We then show that test-retest properties of the experimental measures in our sample of preschool children are in line with the test-retest properties of the same (age-adapted) measures in a sample of young adults. Moreover, the correlations do not vary systematically by socio-economic status. Hence, in empirical models of SES, with preferences as dependent variables, measurement error is likely captured by the error term.

The number of coins put into the piggy bank is our measure of the child's patience, where a higher number implies a higher degree of patience.[17] The average number of coins put into the piggy banks was 5.12, with a standard deviation of 1.62.

### 2.3.2 Risk preferences: coin-flipping experiment

To elicit an overall measure of risk-taking as well as measures of risk neutrality, risk aversion and risk seeking, the children made two choices. Situation A assessed risk aversion. Here, the children could choose between a safe option with a lower expected return and a risky option with a higher expected return. Situation B identified risk seeking. In this situation, the children could choose between a safe option with a higher expected return and a risky option with a lower expected return.

During the experiments, the interviewer presented two coins in each of the two situations. In situation A, one of the coins had three stars printed on each side. The other coin had seven stars on one side and zero on the other. Children chose which coin should be tossed. The interviewer explained that choosing the coin with three stars on each side implied winning three stars for certain. However, choosing the other coin implied that the outcome (seven or zero stars) was determined by chance, with both outcomes being equally likely. The safe amount (three stars) was also "determined" by a coin toss to reduce the likelihood that children did not choose the risky option only for entertainment or game value. After children had made their decision, but before actually tossing the chosen coin, the interviewer presented two more coins in another color (situation B). Now, one coin had four stars on each side, while the other coin again had zero stars on one side and seven on the other. Children made their second decision and the interviewer tossed the two chosen coins. The order in which the two variations of the game (situation A versus situation B) were played was randomized. The coin-flipping experiments is thus a simple, vivid way to assess risk preferences. It is easier to understand than, e.g., a choice list representation commonly used for adults (see, e.g., Holt and Laury, 2002; Dohmen et al., 2010; Charness, Gneezy, and Imas, 2013).

Our main measure of risk-taking is the number of risky choices (zero to four) over the two data collection points in both situations. On average, the number of risky choices is 1.68, with a standard deviation of 1.18.

[17] In a recent methodological contribution on how to measure children's time preferences, Angerer et al. (2015b) compare a choice list measure and a "single choice time-investment-exercise" that is very similar to our piggy bank experiment. The authors show that both measures yield similar aggregate results and substantially correlate within subjects.

In later analyses, we also investigate whether children operate in the risk-averse, risk-neutral, or risk-seeking domain. Children are categorized as risk-averse if they chose the safe option in situation A and situation B (in at least one of the data collection points). Children are categorized as risk-seeking if they chose the risky option in both situations (in at least one of the data collection points). The remaining children, including those who alternated between risk-averse and risk-seeking choices, are categorized as risk-neutral.[18] The corresponding shares are displayed in figure A2.

### 2.3.3 Altruism: three dictator game experiments

Our measure of altruism reflects behavior in three dictator game experiments: one binary choice game and two continuous dictator games with different receivers. In the binary choice game, each child had to decide between two possible allocations of two stars between him-/herself and another unknown child of similar age from the same city (following the experimental protocols by Fehr, Bernhard, and Rockenbach (2008) and Fehr, Rützler, and Sutter (2013)). In one allocation, (2,0), the decision-maker received two stars, while the other child received zero stars. In the alternative allocation, (1,1), both the decision-maker and the recipient received one star each. Both possible allocations were demonstrated to the children and the interviewers checked whether the children had fully understood the implications of each allocation. We also ran two continuous dictator games. In both versions of the game, the interviewers showed the children two paper bags, one belonging to the interviewed child and the other belonging to another child, the receiver. Between games, we varied the receiver. In one game, the receiver is a child living in a nearby city. In the other game, the child lives in an African country. Children knew that the African child does not live together with his parents since they are either "ill or dead". In both versions, children were endowed with 6 stars. After the children had distributed the stars between the two bags, the interviewer checked that they had understood how many stars they and the other child would receive. If the children did not understand the resulting allocation, the rules were explained again and the children could alter their decision. We cooperated with three charity organizations (one in Cologne, Bonn and Togo (SOS Children's Village), respectively) to ensure that the allocation decisions were implemented as described.[19]

[18] Note that our data do not allow a closer view on different degrees of risk aversion in the risk-averse domain.

[19] Our agreement with the charity organizations ensured that the receiving children benefited from the monetary equivalents of the distributed stars in form of toys. This was also communicated to the decision-makers.

The joint measure of altruism is the average share of stars that a child gave away in all six dictator game experiments (three experiments in each of the two data collections). The average share of stars given away is 0.351, with a standard deviation of 0.125.

### 2.3.4 Intelligence (IQ)

Our measure of IQ combines information on crystallized and fluid intelligence. Fluid IQ measures the part of overall IQ that refers to general logical reasoning in new situations, intellectual capacity or processing speed. Crystallized IQ is the part of overall IQ that broadly refers to knowledge that has been acquired in life, such as vocabulary. Following the work of Cattell (1971), these two basic components form general intelligence or simply (overall) IQ.

We rely on IQ tests that are commonly used for children. First, we measured fluid IQ using the matrices test of the HAWIK IV, which is the German version of the well-established Wechsler IQ test for children (Petermann and Petermann, 2010). Children were presented up to 35 blocks or rows of pictures featuring different colors and forms. In every block or row, one cell was missing. Children had to choose which of five pictures best fit into the missing cell. Second, we measured crystallized IQ using the German translation of the commonly-used Peabody Picture Vocabulary Test Revised (PPVT-R) (Dunn and Dunn, 2007).[20] For each item, the interviewer read out one word and showed the child four pictures. Children had to decide which picture best fit the word. For both fluid and crystallized IQ, we separately standardize the average score over both data collections. Our joint measure of IQ is the standardized sum of both subtests.

# 3 SES gaps in child IQ and economic preferences

In this section, we document differences in IQ and economic preferences between elementary school children who grow up in high and low SES families. Our aim is to uncover the importance of SES as an indicator of early disparities in a child's environment, before we turn to the underlying causes and mechanisms.

The gaps in IQ and economic preferences among children from high and low SES households are displayed in figure 1. The horizontal bars represent coefficients of regressions of

[20]Due to time constraints, we had to restrict the test to fourteen items. We chose those fourteen items that had the largest discriminatory power in the SOEP pretest data of the mother and child questionnaires "MukiIIIb" and "MukiIIIc", which were based on a 61-item version of the PPVT-R test (see, e.g., Bartling et al., 2010).

IQ and economic preferences on a dummy variable that equals one for high and zero for low SES households. The figure shows that all our measures of child IQ and economic preferences vary systematically by SES. In particular, children in high SES families have a higher IQ ($p < 0.01$), are more patient ($p < 0.05$), less risk-taking ($p < 0.1$) and more altruistic ($p < 0.05$) than children from families with low SES (see table A2 for the corresponding regression results).[21] The differences by SES are sizable. High SES children have a 65% of a standard deviation higher IQ, are 35% of a standard deviation more patient, 23% of a standard deviation less risk-taking and 21% of a standard deviation more altruistic than their low SES counterparts.

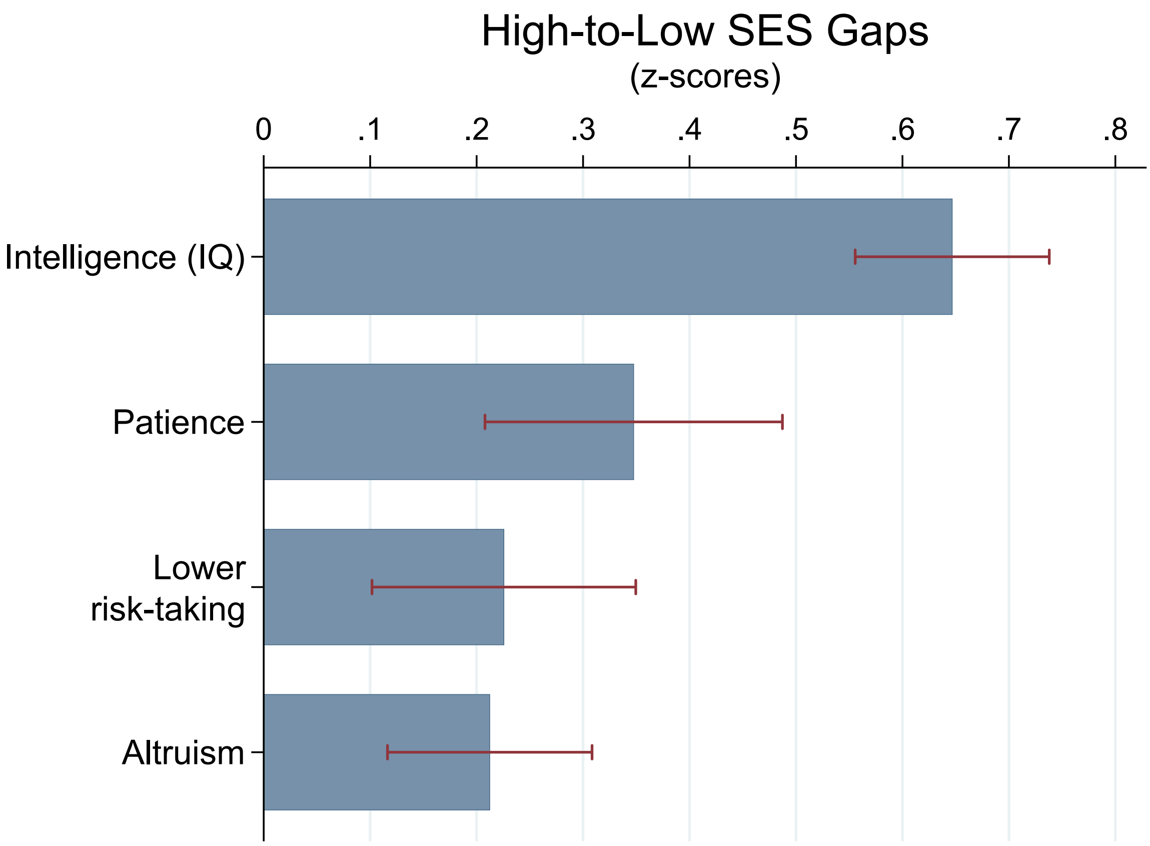



Figure 1: The figure displays gaps in IQ and economic preferences between elementary school children from high and low SES families. The horizontal bars represent coefficients of a dummy variable that equals 1 for high and 0 for low SES households in regressions of IQ or preferences on this SES dummy (OLS for IQ and altruism, Tobit for patience and risk-taking). Error bars show bootstrapped SE (1,000 bootstrap replications).

[21] For comparison, in table A2 we report three different estimates of standard errors (SE). The different estimates are very similar, but bootstrapped SEs are slightly more conservative than OLS or White SEs. Therefore, we report $p$-values based on bootstrapped SE for all regressions in this study.

These effect sizes are substantial when compared to racial gaps, or the impact of most childhood interventions. Regarding patience and IQ, the SES gaps exceed half the size of the black-white achievement test gap in the US (Jencks and Phillips, 1998; Carneiro, Heckman, and Masterov, 2005; Hanushek, 2010). Moreover, the gaps are larger than most of the standardized effect sizes reported for early child care or school-based interventions. In a meta-analysis, Duncan and Magnuson (2013) find a weighted average impact of early child care programs on cognitive and achievement outcomes of 21%, and McEwan (2015) reports average effect sizes of less than 15% of a standard deviation in school achievement for a large number of primary school interventions.[22]

The above-reported gaps in child IQ and preferences are important in light of the literature showing that differences in these characteristics translate into child behaviors and outcomes. Previous studies have documented that children's IQ, patience, risk-taking and prosocial behavior predict success at school (Reynolds, Temple, and Ou, 2010; Almlund et al., 2011; Castillo et al., 2011; Castillo, Jordan, and Petrie, 2015; Almås et al., 2016), while impatience and a high willingness to take risks predict negative health outcomes and risky behaviors, such as smoking or drinking alcohol (Sutter et al., 2013). Importantly, measures of IQ and economic preferences as measured in childhood have also been shown to predict adult outcomes (Strenze, 2007; Borghans, ter Weel, and Weinberg, 2008; Golsteyn, Grönqvist, and Lindahl, 2014). Thus, our key result that gaps in IQ and economic preferences by SES emerge early has wide-ranging implications for important outcomes in childhood, adolescence and adulthood alike.

The results displayed in figure 1 unveil that SES is associated with certain preference and IQ *profiles* in children. For example, children from low SES backgrounds are, on average, less patient *and* more risk-taking; they are less altruistic *and* less intelligent, et cetera.[23] SES thus evokes the simultaneous determination of "risk factors" which favor social immobility and marginalisation. For example, individuals who are both less intelligent and less patient are likely to obtain lower levels of education. Table A3 shows how preference profiles relate to important *teenage* life-outcomes in our data. It displays correlation coefficients between our child preference and IQ measures and teenage life-outcomes from follow-up surveys, collected four to five years after the first data collection (for details on the teenage data see Section B.5). The results indicate that those profiles that prevail in high SES families (high IQ, high patience, low risk-taking, high altruism) translate into

[22] Some high-quality early childhood education programs such as the Perry Preschool or Abecedarian programs show much larger effects, at least in the short run (see Duncan and Magnuson (2013) and Heckman, Pinto, and Savelyev (2013)).

[23] These findings also suggest that SES drives part of the observed preference correlations displayed in table B3. For a discussion of the correlation pattern see Section B.4.

more educational success, more social participation, and less juvenile offending during adolescence.[24] These results also hold conditioning on parental SES (compare panels B and C in table A3).

In the appendix, we show that the high-to-low SES gaps displayed in figure 1 are robust to various alternative specifications. First, we use two different sets of weights in the underlying regressions of figure 1, to make our sample comparable to the German population of families and correct for selective sample attrition. Our results remain very similar when we apply the corresponding weighting schemes (see Section B.1). Second, we add control variables that account for potential SES-related differences in perceptions of the experimental procedures (see Section B.6) and validation of incentives (see Section B.7). Here, we show that our results are unaffected by procedural perceptions, potential in-experimental wealth effects or differential perceptions of the incentives used. Third, we vary the definition of parental education. Our results remain the same whether we rely on measures of maternal education, paternal education or both, suggesting a large degree of assortative mating among spouses with similar educational degrees (see Section B.8). Fourth, we show that the differences in IQ and economic preferences by SES do not significantly differ for boys and girls (see table A4). Last, in table B7 we show that our findings do not change when we account for single parenthood. For a detailed discussion see Section B.9.

Alternatively to using the sum of risky choices as a measure of risk preferences, our data allow classifying behavior in a more fine-grained way. Figure A2 displays the shares of risk-averse, risk-neutral and risk-seeking children by SES. Overall, 44% of the elementary school children in our sample are classified as risk-averse, 32% as risk-neutral and 24% as risk-seeking (compare Slovic (1966) and Falk and Kosse (2016) for similar results). Regarding differences in children's risk preferences by SES, high and low SES children are about equally likely to be risk-averse (43.3% vs. 44.4%, $p = 0.814$, see table A5). However, a higher share of high SES children are risk-neutral (36.1% vs. 28.2%, $p < 0.1$), whereas a higher share of low SES children are risk-seeking (20.6% vs. 27.4%, $p < 0.1$). Hence, our finding that low SES children are significantly more risk-taking than children from high SES families does not originate from high SES children being more risk-averse, but rather from low SES children being more risk-seeking as opposed to risk-neutral.[25]

[24] For recent evidence on the relation of skills/personality and political or social participation see Hufe and Peichl (2016) and Holbein (2017).

[25] Similarly, using breastfeeding duration as a measure of favorable conditions within a child's family, Falk and Kosse (2016) find that children who are breastfed for a shorter period of time are more prone to take risks during preschool age.

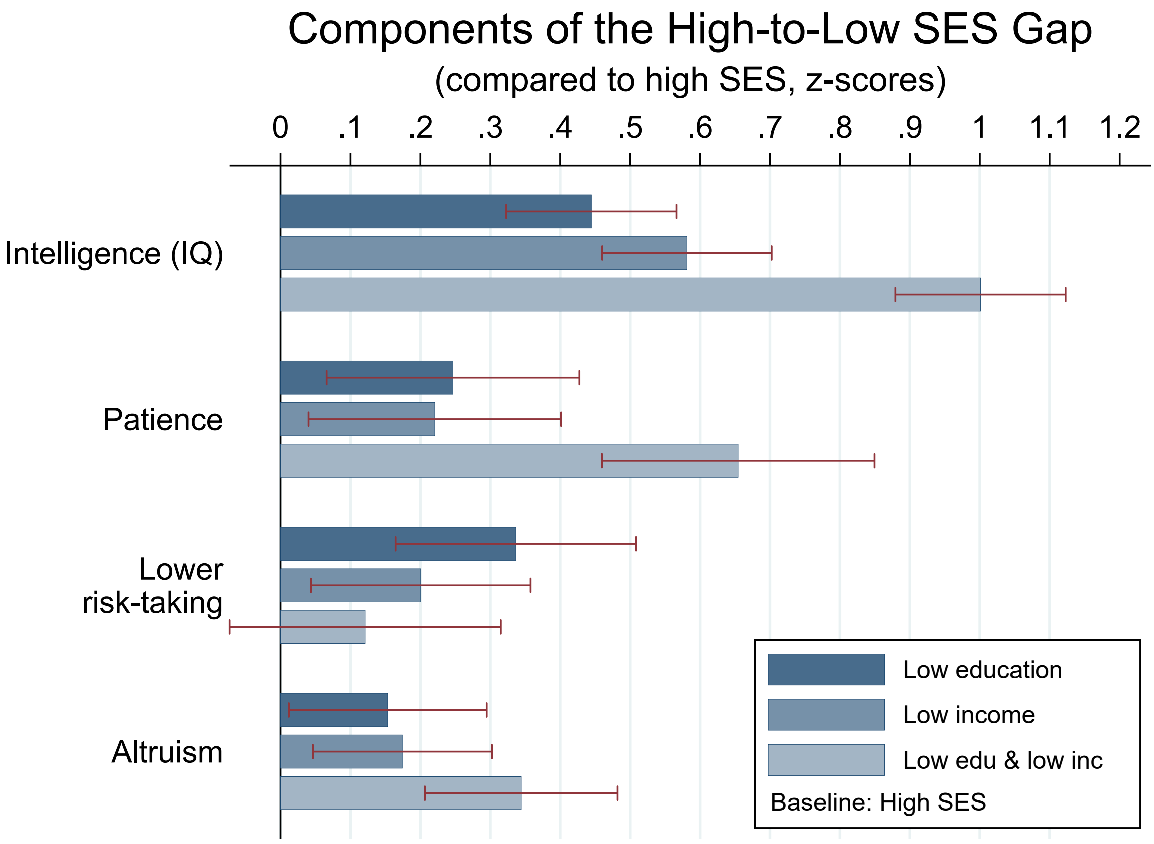



Figure 2: The figure displays gaps in IQ and economic preferences between elementary school children from different socio-economic backgrounds. The horizontal bars represent coefficients of three dummy variables in regressions of IQ or preferences on the three dummies (OLS for IQ and altruism, Tobit for patience and risk-taking). The first dummy variable equals 1 for a parental background that is characterized by low education but an income above the low SES threshold and 0 otherwise. The second dummy variable equals 1 for a parental background that is characterized by low income but a level of parental education exceeding the low SES threshold and 0 otherwise. The third dummy variable equals 1 if both low SES criteria are met (low income and low parental education) and 0 otherwise. The displayed coefficients indicate differences between each respective low SES subgroup and the baseline category of high SES (neither low parental education nor low income). Error bars show bootstrapped SE (1,000 bootstrap replications).

The results on SES gaps presented thus far rely on a definition of SES that classifies households as low SES if they meet at least one of two criteria (low household income and low parental education). This reflects our sampling scheme. Nonetheless, to better understand which components of low SES matter, we also decompose the overall gap into the parts that are explained by low education and/or low income, respectively. We repeat the analysis shown in figure 1, but now sub-divide the low SES category into (i) low parental education only, (ii) low parental income only and (iii) both low parental education and low parental income. The gaps between children from these three groups and those from high SES families are presented in figure 2. It shows that children from high SES families score higher on IQ tests, are more patient, less risk-taking and more altruistic than children from low SES families regardless of whether we use low income only, low education only or a combination of both. Moreover, if both low income and low parental education are present in a single family, the SES gaps in IQ, patience and altruism are largest, suggesting that low income and low parental education are "risk factors" that reinforce each other.

Table A6 complements the analysis shown in figure 2 by using income and education as continuous variables. We regress IQ and economic preferences on average years of parental education, household income and their interaction. The results largely confirm the pattern shown in figure 2. More education and income are related to higher IQ, patience and altruism as well as less risk-taking of children. The effect is most pronounced for IQ and on a similar level for time, risk and social preferences. The interaction effects are usually relatively small compared to the main effects (except for patience) which indicates that the low SES effect is pronounced for children from families that have low levels of education and low income.

# 4 SES and the development of preferences and IQ: a conceptual framework

In the previous section, we have shown that parental SES is a powerful predictor of a child's IQ and economic preferences. In this section, we present and estimate a framework, inspired by the model of Becker and Tomes (1986) as well as the technology of skill formation (Cunha and Heckman, 2007; Cunha, Heckman, and Schennach, 2010), concerning how maternal IQ and preferences, household income, education and parental investments affect a child's IQ and preferences. Given the cross-sectional nature of our data, we cannot estimate a fully dynamic model in which children's IQ and preferences are a function of last period's levels, and in which parents adapt their investments over time. Instead, we present a static framework and approach potential endogeneity by collecting measures on the parental assessment of their children's development. Relying on this approach, we approximate the process of a child's IQ and preference development until mid-childhood. In this respect, our framework can be thought of as an application of Becker and Tomes (1986) for one particular period of childhood, where initial endowments are captured by maternal IQ and preferences.

## 4.1 The formation of child IQ and preferences

We model the formation of a child's IQ and preferences as a function of maternal IQ and preferences and parental investments. Moreover, we allow the productivity of this process to vary across high and low SES families.

Child development is represented by a four-dimensional vector of IQ, patience, lower degrees of risk-taking and altruism denoted by $P_i = (P_i^{IQ}, P_i^P, P_i^R, P_i^A)$. In line with the literature on the technology of skill formation (Cunha, Heckman, and Schennach, 2010), we assume that IQ and preferences are formed according to a production function with Constant Elasticity of Substitution (CES), which we write as:

$$P_i^\ell = \Pi_{\text{SES}}^\ell [\gamma_M{}^\ell M_i^{\ell\phi^\ell} + \gamma_s{}^\ell I_i^{S\phi^\ell} + \gamma_t{}^\ell I_i^{T\phi^\ell}]^{\frac{1}{\phi^\ell}} e^{\eta_i^\ell} \qquad \ell \in \{IQ, P, R, A\}, \tag{1}$$

where $\gamma_j^\ell \in [0,1]$ are production shares, such that $\sum_j^J \gamma_j^\ell = 1$. $\phi^\ell \in [-\infty, 1]$ is an elasticity parameter and $\varepsilon = 1/(1-\phi^\ell)$ represents the elasticity of substitution in the inputs that generate IQ and preferences. Moreover, $e^{\eta\ell}$ reflects unobserved random shocks. Factor inputs are as follows: $M^\ell$ denotes the maternal characteristic that corresponds to $P^\ell$, $I^S$ is a positive parenting style and $I^T$ denotes time investments. $M^\ell$ enters the production function to capture the direct transmission of IQ and preferences, which can take place socially or genetically. Our data do not allow to distinguish between social, genetic, or other factors in the direct transmission of IQ and preferences through $M^\ell$. However, as an example, one may imagine that if a mother acts very altruistically, the child likely imitates that behavior.[26]

$\Pi_{\text{SES}}$ in equation (1) denotes a factor-neutral SES-specific productivity parameter. It captures productivity differences that arise if, for example, the same amount of inputs yields a larger amount of output in high rather than low SES families (in which case, $\Pi_{\text{SES}} > 1$).

[26]For descriptive evidence on an intergenerational transmission of preferences, see Kosse and Pfeiffer (2012, 2013) for evidence on patience, Dohmen et al. (2012) and Alan et al. (2017) for risk-taking and Kosse et al. (2019) for social preferences.

Such productivity differences may arise, for example, if a certain level of investment by a highly-educated or affluent mother is more productive than the same investment by a less educated or poor mother.

Note that all parameters of the above function may differ across preferences and IQ. Thus, for each characteristic $P^\ell$ the substitutability of inputs may vary freely from perfect complements ($\phi^\ell \rightarrow -\infty$) to perfect substitutes ($\phi^\ell \rightarrow 1$). Along the same lines, the production shares ($\gamma$) and the factor-neutral productivity parameter may vary freely across characteristics.

The above production function focuses on parenting style, parental time investments and maternal characteristics as key inputs. Other factors, such as material wealth, the abundance of consumer products, or the quality of housing are not explicitly modeled and may only enter via these factors or via $\Pi_{\text{SES}}$. The focus on parental time and style investments is motivated by a large literature in psychology which puts interactions with caregivers at the forefront of child development (e.g., Bowlby, 2008; Eisenberg, Spinrad, and Knafo-Noam, 2015; Rogoff, 1990; Skinner, 1953).[27] Yet other determinants of child IQ and preferences are likely captured in $M$. Examples are the genetic disposition of the mother with respect to any of the characteristics $\ell$, or her role model behavior. The focus of the above equation is thus the relationship between parental SES, parental investments, and child IQ or preferences. Additional information on the different components of $M$ would be required to capture how, e.g., social, genetic, and other factors (differentially) affect both SES and the productivity parameter $\Pi_{SES}$.

## 4.2 Parental investment and the determinants of SES

Recent empirical studies (Cunha and Heckman, 2007; Heckman, 2008; Heckman and Mosso, 2014; Doyle et al., 2017) stress the importance of parental investments in children. Such investments can take various forms, as any parent-child interaction represents some kind of "investment" into the child's human capital. We think of parental investments along two dimensions: parenting styles and parental time investments. First, the type of parental interactions such as the tone and attitude by which parents approach their children is termed "parenting style" (denoted by $S$), reflecting the quality of parent-child interactions. Doepke and Zilibotti (2017) present a theoretical model in which they argue that parenting style depends on the socio-economic environment in which a family lives and that parenting style may affect children's preferences. Moreover, Burton, Phipps, and Curtis (2002) show

[27]For evidence on the role of role models and interaction for the development of prosociality, see Kosse et al. (2019).

that both socio-economic factors and parenting style are important determinants of child behavior. Second, we focus on time-intensive high-quality parent-child interactions (denoted by $T$), termed "time investments". Time investments capture the so-called "quality time" that children spend with their parents (Price, 2008; Guryan, Hurst, and Kearney, 2008).

Investments are a natural candidate of how SES translates into differences in IQ and preferences. In order to capture this mechanism, we specify a simple investment system to approximate the underlying structural model of parental investment decisions. According to this model, parental investments are determined by household characteristics, maternal characteristics as well as SES:

$$I_i^m = \delta_0^m + \delta_M^m M_i^P + \delta_{\text{SES}}^m \text{SES}_i + \delta_{X_i}^m X_i + \epsilon_i^m \qquad m \in \{S, T\}, \tag{2}$$

where $M^P$ denotes a vector of maternal IQ and preferences, SES comprises education and income as measures of socio-economic status and $X_i$ is a vector of household characteristics. $\epsilon_I^m$ with $m \in \{S, T\}$ are error terms, which may correlate across investment equations. In addition, as discussed in the next section, $\epsilon_I^m$ may correlate with ${\eta_i}^\ell$, i.e., as parents react to shocks in the development of their children.

By specifying equations (1) and (2) of the above framework, we allow SES to affect a child's IQ and preferences through two main channels. First, parental education and household income can have a direct effect on the level of parental investments (*level effect*). For example, more educated parents tend to spend more quality time with their children (see, e.g., Guryan, Hurst, and Kearney, 2008). Similarly, high-income families may find it easier to comfort and reward their children (in particular if rewards are costly) rather than punishing them (Weinberg, 2001). They also have the resources available to replace their time for more basic tasks such as house cleaning, gardening, or driving kids to school, freeing up time for more high-value interactions with children (see, e.g., Doepke and Zilibotti, 2019). Second, the effect of parental investments may differ by SES if education or material resources interact with the amount and quality of parental investments. This *productivity effect* is captured by $\Pi_{\text{SES}}$ in equation (1). Mothers in turn can use their IQ and preferences to produce education and household income. Section B.10 describes this relationship.

## 4.3 Estimation strategy

### 4.3.1 Parenting style and time investments

This section explains how we measure parenting style and time investments (for further details, see Section B.11.1).[28] First, we elicit parenting practices ($\mathcal{M}^S$) through several questionnaire items that can be grouped in a measure of parental warmth (comprising praise and emotional warmth), a measure of parental interest and monitoring, and a measure of parental psychological and behavioral control (punishment). Parenting style does not follow a natural metric and is assumed to be latent, but known to the mothers. We thus employ a measurement model with a flexible distributional factor structure in form of a mixture distribution to extract latent parenting style, where a higher value reflects warm and child-oriented parenting but also a high degree of monitoring, while a lower value is associated with a higher degree of punishment (for details, see Section B.13). Second, in addition to parenting style, we account for parental time investments. Parental time investment can be thought of as the quantity of parental interactions and it is measured in terms of the share of total time that parents and children spend together on highly interactive activities (talking/discussing, having a meal together, playing outside, board games, reading to the child, playing an instrument together). Using the share of time devoted to highly interactive activities allows us to hold the maternal time budget for non-work related activities fix, which might itself be a function of other familial contexts, such as the number of children or the number of available caregivers.[29] For details, see Section B.11.1.

### 4.3.2 Production function

Aside from precise measures of parenting styles and time investments, our data are characterized by two exceptional features, which we exploit in our empirical specification of the model. First, they contain very precise measures of preferences and IQ for both mothers and children. All preference measures of children are interpretable in terms of decision-making behavior in incentivized experiments (Section B.2 provides details on our measures of maternal IQ and preferences). Second, stratified sampling of our data by education and income allows for a clear distinction between high and low SES families. In line with the sampling scheme, we define a low SES group ($SES = 0$) and a high SES group ($SES = 1$), as in the first part of this paper (for details, see Section 2.2). We use this definition in our

[28] Our analysis relies on the assumption that maternal responses about inputs proxy parental investments more generally. In Section B.12, we discuss the related literature and use SOEP data to verify this claim.

[29] This approach is in line with the findings reported in Hsin and Felfe (2014), i.e., that high SES mothers tend to substitute highly interactive activities for detrimental activities.

model to investigate whether there are productivity differences in the formation of preferences and IQ across high and low SES families. We then use our estimates to investigate how the SES gap documented in figure 1 would change in response to policies aiming to raise household income, parental education or parental investments.

In order to empirically estimate equation (1), we take the natural logarithm to obtain:

$$\ln(P_i^\ell) = \ln(\Pi_{\text{SES}}^\ell) + \frac{1}{\phi^\ell} \ln\left[\gamma_M^\ell M_i^{\ell\,\phi^\ell} + {\gamma_s}^\ell I_i^{S^{\phi^\ell}} + {\gamma_t}^\ell I_i^{T^{\phi^\ell}}\right] + \eta_i^\ell, \tag{3}$$

for all $\ell \in \{IQ, P, R, A\}$. To ensure that our measures of maternal IQ, preferences and time investments are non-negative, we follow Cunha, Heckman, and Schennach (2010) and assume that each measure in our data represents the natural logarithm of the original (standard normalized) characteristic entering equation (1). Along the same lines, we assume that our measures of parenting styles are proxies of the natural logarithm of the underlying parenting factor. $\Pi_{\text{SES}}^\ell$ denotes a factor-neutral productivity parameter, which we assume to equal unity for low SES families and which may vary freely for high SES families. $\Pi_{\text{SES}}^\ell$ thus captures any productivity differences across socio-economic status that are not due to level differences in investments or maternal IQ and economic preferences.

### 4.3.3 Investment endogeneity

Estimates of the above production function are biased if the parental investments, parenting style and quality time respond to unobserved developmental shocks. This endogeneity may arise if parents compensate or reinforce recent shocks to their child's development that are unobserved to the researcher but observable to the parents.[30] Cunha, Heckman, and Schennach (2010) model the unobserved heterogeneity as latent variables, while Attanasio et al. (2015) employ a control function approach. Due to the small size of our sample and because we focus on two different types of parental investments, we follow a different strategy.[31] Specifically, we assume that the error terms in equations (1) and (2) are additively separable in a part that captures the parental reaction to shocks and an idiosyncratic random shock:

$$\begin{aligned} \eta_i^\ell &= \gamma_\alpha^\ell \alpha_i + \varepsilon_i^\ell \\ \epsilon_i^m &= \delta_\alpha^m \alpha_i + \nu_i^m, \end{aligned} \tag{4}$$

[30] For a discussion, see Cunha, Heckman, and Schennach (2010) and Attanasio et al. (2015).

[31] By sampling design, our sample is very homogenous in age and place of residence, such that contextual variation cannot be used as exclusion restriction.

where $\eta_i^\ell \sim N(0, \sigma^{2\ell})$ and $\epsilon_i^m \sim N(0, s^{2m})$. Moreover, all idiosyncratic random shocks are assumed independent across equations and orthogonal to $\alpha_i$. Under these assumptions, the error terms across investment and technology equations are only related due to differences in parental perceptions about their children's development. In our parent survey we collected measures of $\alpha_i$, which we use according to equations (4) to deal with potential endogeneity issues (see Section B.11.2 for details).

## 4.4 Results: model estimates

Figure 3 displays kernel density plots of the logarithm of the estimated parenting style as well as time investments to illustrate differences between high and low SES families. For both dimensions of parental investments, we find large and significant differences by parental SES, with a larger difference for time investments than for parenting style.

Figure 3: Parental Investments by Socio-economic Status

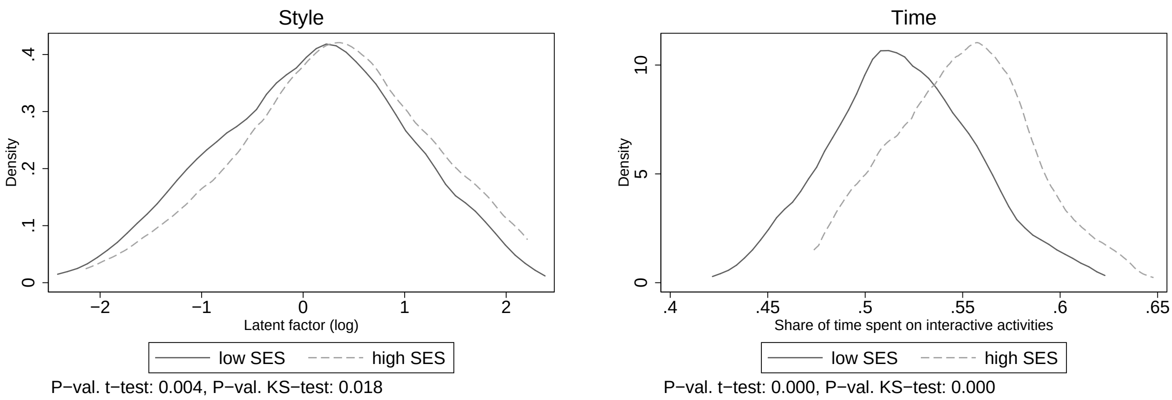



Table 1 displays the results of the parental investment system (equation (2)). Accounting for potential endogeneity of investments in terms of satisfaction with child development, both a positive parenting style and parental time investments are significantly related with SES. However, the respective channels through which SES affects either investment differ markedly: while parenting style is almost exclusively related to household income, parental time investments are more strongly predicted by parental education. We can only speculate about the mechanisms behind these findings. For example, one could plausibly argue that a higher level of household resources facilitates a positive parenting style if resources enable parents to reward rather than punish their children (see Weinberg, 2001, for a model along these lines). In addition, a higher household income likely reduces parental stress, which may increase parental warmth and reduce (unfair) punishments. On the other hand, a higher level of education may be associated with increased knowledge about the benefits of close interactions with the child in terms of their positive effects on child human capital development. Single parenthood proves largely unimportant for parental investments in our data (for a discussion, see Sections B.9 and B.12).

Table 1: The relationship between SES and parental investments

| | Parental Investments | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Style | | Time | | Style | | Time | |
| **SES** | | | | | | | | |
| High SES | 0.224** | (0.091) | 0.646*** | (0.095) | | | | |
| Parental education | | | | | 0.018 | (0.019) | 0.117*** | (0.018) |
| Log HH income | | | | | 0.311*** | (0.118) | 0.178 | (0.111) |
| **Satisfaction child devt.** | | | | | | | | |
| $\delta_\alpha$ | 0.130*** | (0.034) | 0.014 | (0.031) | 0.127*** | (0.033) | 0.013 | (0.030) |
| Observations | 435 | | 435 | | 435 | | 435 | |

**Notes**: Standard errors (in parentheses) are bootstrapped using 1,000 bootstrap replications. Further control variables comprise maternal preferences and IQ, child age, the overall number of children in the household and an indicator of single parenthood. The coefficient for single parenthood is small and insignificant in all specifications (coef/p.val: 0.0955/0.335, 0.004/0.968, 0.135/0.200, 0.001/0.990). Significance at * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 2 reports the estimates of the CES production function. The table presents the estimated coefficients for inputs, the productivity parameter $\Pi_{SES}$, the elasticity parameter $\phi$ from equation (1) and the elasticity of substitution in the inputs that generate child IQ and preferences. Several important features of child development stand out. First, we find that maternal characteristics are important for the development of child characteristics. This indicates that mothers transmit their own preferences and IQ to their children either genetically or through serving as a role model (Dohmen et al., 2012; Alan et al., 2017) or both. Second, both a positive parenting style and time inputs matter for child development. Third, the productive efficiency of the developmental process does not substantially vary by the socio-economic status of the parents, as $\Pi_{SES}$ is close to one in all models. This finding is key, as it suggests that the socio-economic differences in child IQ and preferences documented in the first part of the paper are mostly due to differences in inputs. In other words, if low SES families were to provide the same inputs in terms of maternal IQ and preferences, parenting styles and time investments, they would "produce" children with similar preferences and IQ as high SES families. In fact, after accounting for investments and maternal preferences, low SES families are slightly more efficient when it comes to the production of lower risk-taking, patience and altruism. This finding also suggests that our model does not leave out other important inputs, related to unmodeled factors such as the availability of consumer products or the quality of housing. If at all, these factors seem to "tilt" our results towards smaller gaps for low SES children through $\Pi_{SES}$. Fourth, the elasticity of substitution in inputs is larger than one for the development of IQ, and slightly larger than (but close to) one for economic preferences. This result has important implications for policy, as it suggests that a policy that raises only one type of input (e.g., maternal time inputs) would be effective even if all other inputs were kept unaltered. Although our model is arguably much simpler, our findings regarding the elasticity of substitution in inputs for IQ are in line with those reported in Cunha, Heckman, and Schennach (2010) given that our developmental stage lies between the ones that they investigate.

Table 2: Production function estimates

| | **IQ** | **Patience** | **Lower risk-taking** | **Altruism** |
|---|---|---|---|---|
| **SES productivity** | | | | |
| $\Pi_{SES}$ | 1.082 | 0.860 | 0.733 † | 0.893 |
| | (0.108) | (0.101) | (0.097) | (0.096) |
| **Inputs** | | | | |
| $M^{\ell}$ | 0.429*** | 0.349*** | 0.255*** | 0.344*** |
| | (0.052) | (0.056) | (0.054) | (0.052) |
| Style | 0.271*** | 0.285*** | 0.306*** | 0.329*** |
| | (0.047) | (0.054) | (0.057) | (0.053) |
| Time | 0.301*** | 0.367*** | 0.439*** | 0.327*** |
| | (0.047) | (0.053) | (0.049) | (0.048) |
| **Satisfaction with child development** | | | | |
| $\gamma_{\alpha}$ | 0.984 | 0.985 | 0.987 | 0.990 |
| | (0.008) | (0.012) | (0.078) | (0.009) |
| **Elasticity** | | | | |
| $\phi$ | 0.338* | 0.253 | 0.046 | 0.155 |
| | (0.178) | (0.286) | (0.195) | (0.193) |
| $\varepsilon$ | 1.511 | 1.340 | 1.049 | 1.183 |
| | (0.414) | (0.491) | (0.219) | (0.197) |
| Observations | 435 | 435 | 435 | 435 |

**Notes**: $\varepsilon = 1/(1-\phi^{\ell})$ represents the elasticity of substitution in the inputs that generate IQ and preferences. The reported SE (in parentheses) were bootstrapped using 1,000 bootstrap replications. *** indicates statistical significant difference from zero at the 1 % level, ** indicates statistical significant difference from zero at the 5 % level, * indicates statistical significant difference from zero at the 10 % level. † indicates statistical significant difference from one at the 1 % level.

It is difficult to interpret the size of the estimated coefficients given the non-linear setup of the model, which ensures that the degree to which different parental investments map into child outcomes depends on the estimated elasticity. Therefore, we present average marginal effects in table 3 to illustrate the average effect of a one standard deviation increase in inputs on child IQ and preferences. We find that the biological or social heritability of maternal characteristics is largest for IQ and smallest for risk preferences. This result is in

Table 3: Production function (average marginal effects)

| **Marginal effects** | **IQ** | **Patience** | **Lower risk-taking** | **Altruism** |
|---|---|---|---|---|
| $\text{AME}_{M^{\ell}}$ | 0.585*** | 0.442*** | 0.374*** | 0.554*** |
| | (0.084 ) | (0.099 ) | (0.069 ) | (0.114 ) |
| $\text{AME}_{\text{Style}}$ | 0.313*** | 0.343*** | 0.445*** | 0.424*** |
| | (0.074 ) | (0.090 ) | (0.093 ) | (0.069 ) |
| $\text{AME}_{\text{Time}}$ | 0.367*** | 0.464*** | 0.449*** | 0.436*** |
| | (0.072 ) | (0.120 ) | (0.107 ) | (0.085 ) |
| Observations | 435 | 435 | 435 | 435 |

**Notes**: The reported SEs (in parentheses) were bootstrapped using 1,000 bootstrap replications. Significance stars at * p < 0.1, ** p < 0.05, *** p < 0.01.

line with findings from a large body of literature on the heritability of IQ, which documents that IQ is strongly transmitted from parents to children (Black, Devereux, and Salvanes, 2009). Time and style investments are of similar importance for IQ and altruism. However, regarding time and risk preferences, time investments are relatively more important than style investments.[32]

Our results are robust with respect to alternative model specifications. We start out by investigating if single parenthood is sufficiently accounted for. First, to capture potential direct effects of lone motherhood we include a single parenting indicator variable as an additional covariate to equation (3). Then, to assess potential heterogeneities in the production process, we also restrict our sample to two-parent families. The corresponding results are displayed in table B8 and discussed in Section B.9. The estimated effect sizes hardly change when single parenthood enters as a control variable and even when we restrict the sample to two-parent households, our results remain largely unaltered, except for a slight increase in the importance of parenting styles. These results are in line with a literature showing that single parenthood is far more detrimental for child outcomes in the US (McLanahan, 2009) than in Germany (Francesconi, Jenkins, and Siedler, 2010; Woessmann, 2015). We proceed our robustness analysis by loosening the assumption that only one respective maternal trait may affect child IQ and preferences. Yet, by including other maternal characteristics into the model, we find no evidence of direct effects (see table B14 of Section B.15) nor differences in productivity among high and low IQ mothers (see table B15). Hence, high IQ mothers do not seem to have an easier time producing child preferences than low-IQ mothers in our data. Last, we investigate how the aggregation of parenting styles and time investments affects our results. As for parenting styles, alternative ways to

[32] In figure B3 of Section B.14, we use the estimates reported in table 2 to show graphically how a change in parental investments (by ventile) affects children's IQ and preferences.

aggregate parental responses lead to different results if parental behaviors translate into IQ and preferences differentially, or if the presence of covariates in the measurement system affects our estimates. If we use principal factor analysis without covariates and Bartlett (1937) scores, we find a somewhat smaller SES gap in parenting styles (see Section B.13). Moreover, the impact of parenting styles on child IQ and preferences slightly reduces for IQ, patience, and risk taking. It remains similar for altruism. Regarding parental time investments our results remain similar when we use the absolute number of highly interactive activities as an alternative measure of parental time investments. There is, however, more variability in the absolute number of interactive activities among low SES than among high SES families and the estimated relationship of this measure with child outcomes is somewhat weaker (see Section B.16 for results and a discussion).

## 4.5 Policy implications

The above model of the relationship between maternal IQ and preferences, investments, SES and child IQ or preferences is complex in the sense that the CES production function is highly non-linear. Moreover, the levels of investment also relate to SES. Consequently, the above-reported coefficients are relatively uninformative when it comes to policy implications. Hence, whilst keeping in mind the above set of assumptions and the limitations of our one-period model, we use our model estimates to predict outcomes and make statements about potential policy effects. Two types of family policies are conceivable to reduce socio-economic disparities in child development: (i) policies that change the amount of resources available to low SES families, through either an increase in parental education or income subsidies, whereby examples are compulsory education laws or anti-poverty policies such as the earned income tax credit in the US (see, e.g., Oreopoulos, Page, and Stevens, 2006; Dahl and Lochner, 2012); (ii) policies that enhance parental investments among low SES families, for example, through home visiting programs that target parental investments. Recent evidence shows that home visiting programs are indeed effective in raising parental investments (Gertler et al., 2014; Attanasio et al., 2015; Baranov et al., 2016; Doyle et al., 2017; Heckman et al., 2017).[33] For example, Baranov et al. (2016) find an effect of 20% of a standard deviation on time-intensive investment, while Heckman et al. (2017) report effect sizes of 0.27-0.37% of a standard deviation on non-abusive parenting attitudes and of up to 0.18% of a standard deviation on maternal emotional and verbal responsivity. We thus conclude that an increase in parental investments of around 20% of a standard deviation

[33] To the extent that maternal investments can be substituted for by professional care-givers, high-quality early child care programs might also apply here (Heckman, 2011; Heckman, Pinto, and Savelyev, 2013).

might be realistic in terms of the effect size that a large-scale parental investment policy can achieve.[34]

We investigate how five different policies would change the IQ and preference development of children from low SES families. For this purpose, we take our model estimates as given and predict counterfactual outcomes for the respective group of individuals who would be affected by a certain policy. The five different policies are:

1. A compulsory schooling policy that requires both parents to obtain 13 years of education (A-level equivalent).
2. A policy that provides (tax-neutral) income support to poor families. All family net equivalence incomes are raised to the threshold level of 1,065 EUR.
3. A policy that raises parenting style investments by 20% of a standard deviation.
4. A policy that raises parental time investments by 20% of a standard deviation.
5. A policy that raises both parenting style investments and parental time investments by 20% of a standard deviation.

[34]Another policy would be to enhance maternal IQ and preferences. Note, however, that such a policy would be very long-term. Moreover, understanding its ramifications would require a more explicit model that captures the malleability of different maternal characteristics and their relation to SES.

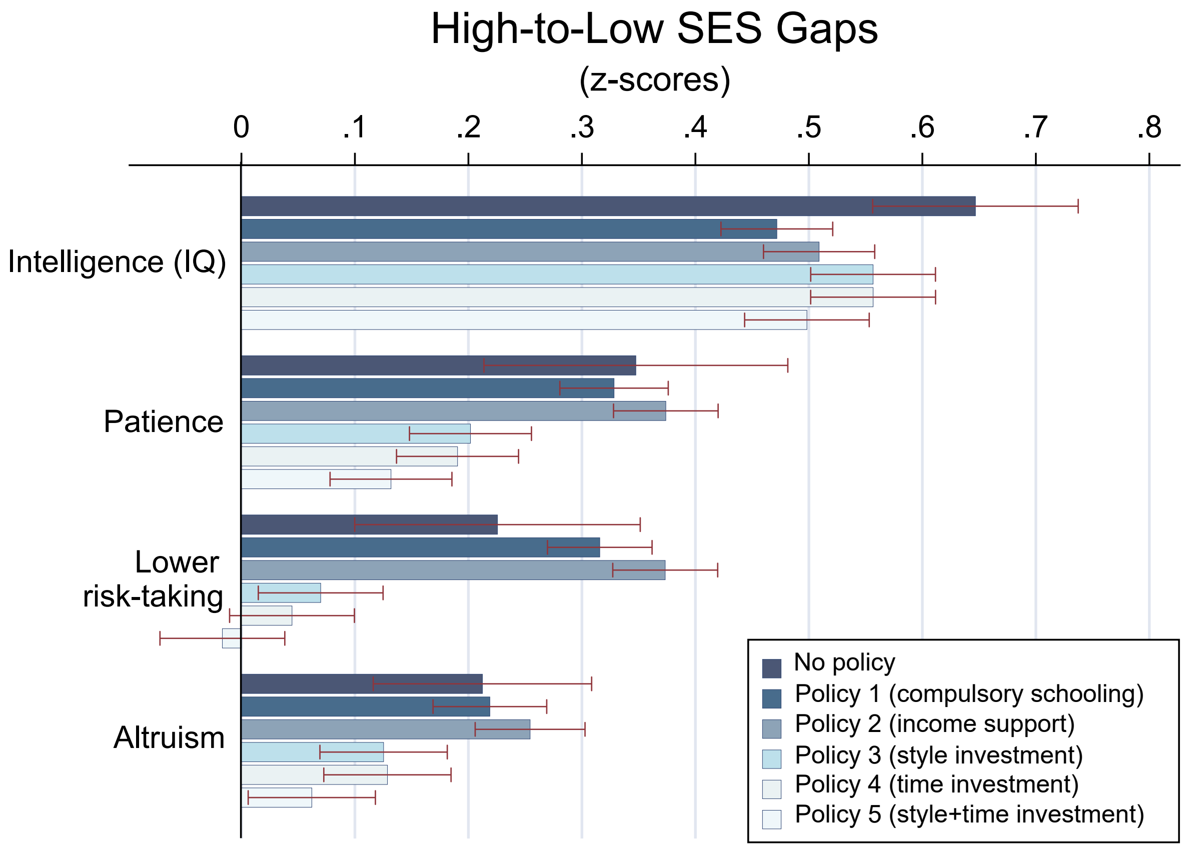



Figure 4: The first bars show the results of the main analysis, see figure 1. The other bars show gaps in IQ and economic preferences between elementary school children from high SES and low SES families, as they would occur if the respective policy was put in place. In order to estimate the effects, IQ and preferences are regressed on the SES dummy. Error bars show bootstrapped SEs.

Figure 4 provides a graphical representation of what the SES gaps would look like in the presence of each of the five policies (bars 2-6 in each panel) when compared to the raw SES gap documented in figure 1 (top bar in each panel).[35] We find that an increase in parental education and family income would be most effective in closing the SES gap in IQ.[36] This result is in line with, e.g., Dahl and Lochner (2012), who find a positive effect of income support on children's academic achievement, and Lindqvist and Vestman (2011), who find that an extension of maternal compulsory education in Sweden increased child IQ. Regarding preferences, the impact of a respective compulsory schooling or income support policy on patience, risk preferences and altruism would be small or even negative. The intuition for this result is that these policies would reduce the investment gap by relatively

[35] All corresponding estimates are displayed in table A7.

[36] We allow education to affect income using the estimates reported in table B10.

little (see rows 3-4 of table A7) and that the positive level effect would be countervailed by a negative productivity effect. Figure 4 also shows that a direct change in parental investments (policies 3-5) would have a substantial positive effect on children from low SES families, in particular with respect to economic preferences. A policy that raised both parenting style investments and parental time investments by 20% of a standard deviation would nearly close the SES gap for patience and altruism, while it would fully close the gap for risk-taking. The gap in IQ, i.e., the trait for which maternal IQ is particularly important (but unchanged), would only decrease by around 15%.[37]

# 5 Discussion and conclusion

Our results show that SES is a systematic predictor of a child's IQ and economic preferences. Already during elementary school, children from families with higher SES score higher in IQ tests, are more patient, less risk-taking and more altruistic. The SES gaps in IQ and economic preferences are of sizable magnitude and remain similar when representative population weights are applied. The overall pattern of results suggests that childhood circumstances cumulate, given that low parental education and low parental income a fortiori affect the formation of preferences and IQ if both are present in a single family. In order to understand the underlying mechanisms, we provide a coherent framework of how parental investments and maternal IQ and preferences influence child outcomes in which SES can influence both the level of investments and their overall productivity. Within this framework, we can show that disparities in the level of parental investments hold substantial importance regarding the SES gaps in economic preferences and, to a lesser extent, IQ.

For patience and IQ, there exists abundant evidence showing that higher levels favor important outcomes in life since they are associated with higher levels of education (Shoda, Mischel, and Peake, 1990; Heckman and Vytlacil, 2001; Cadena and Keys, 2015), income (Heckman, Stixrud, and Urzua, 2006; Hanushek and Woessmann, 2008; Golsteyn, Grönqvist, and Lindahl, 2014) and better health (Chabris et al., 2008; Sutter et al., 2013; Golsteyn, Grönqvist, and Lindahl, 2014).[38] Moreover, altruism is positively associated

[37]We are unaware of any other studies investigating the impact of parental investments on child economic preferences. However, our findings are somewhat in line with literature showing that non-cognitive traits are often more easily malleable than cognitive traits in response to an exogenous change in investments (see, e.g., Heckman, Pinto, and Savelyev, 2013).

[38]Concerning attitudes towards risk, there is no obvious optimal degree of risk aversion that is independent from the environment in which an individual lives. Doepke and Zilibotti (2017) introduce the distinction between endogenous and exogenous risk to which individuals are exposed. While exogenous risks cannot be avoided, taking an endogenous risk is a deliberate decision that depends on the individual risk attitude. Moreover, with respect to endogenous risks, it is difficult to claim that there is an "optimal"

with success of groups and cooperative behavior in various domains of life as well as with individual life satisfaction (Rustagi, Engel, and Kosfeld, 2010; Carpenter and Seki, 2011; Becker et al., 2012; Aknin et al., 2013; Burks et al., 2016). In this sense, our results suggest that, on average, children from families with lower SES are disadvantaged.

Differences in children's preferences and IQ are important as they predict functioning in childhood as well as adult outcomes. In particular, children's IQ and social behavior are positively correlated with their success at school (Reynolds, Temple, and Ou, 2010; Almlund et al., 2011). Among children and adolescents, impatience is associated with a higher likelihood of drinking alcohol and smoking, a higher body mass index, a lower propensity to save, worse grades, more disciplinary conduct violations at school and a lower likelihood to complete high school in time (Castillo et al., 2011; Castillo, Jordan, and Petrie, 2015). Like adults, more risk-averse children and adolescents are less likely to be overweight or obese (Sutter et al., 2013). Moreover, Moffitt et al. (2011) argue that childhood differences in preferences determine later life outcomes for two reasons: first, they affect the accumulation of later skills and preferences through self-productivity and cross-fertilization (Heckman, 2007); and second, they are decisive because they affect early decisions, which can have irreversible and lasting effects. As an example, higher levels of self-control and patience among teenagers are associated with a lower prevalence of school dropout, substance abuse and unplanned pregnancies. In this respect, our results contribute to literature showing that gaps in economic opportunities open up early in life (Case, Lubotsky, and Paxson, 2002; Heckman, 2007).[39]

Given that patience, risk-taking and altruism determine the shape of the utility function, our results also have implications for economic modeling. First, we show that individuals already systematically differ in economic preferences at relatively young ages. It may thus be beneficial to capture these heterogeneities in theoretical or empirical models of economic decision-making, e.g., regarding school choice or the engagement in risky behaviors. Second, differences in socio-economic conditions shape economic preferences, which in turn determine economic decision-making and outcomes, suggesting that preferences and IQ are

level of risk attitude. For example, Dohmen et al. (2011) document that a higher willingness to take risks is associated with behaviors that are typically perceived as both detrimental (e.g., smoking) or supportive to good health (e.g., exercising).

[39]Using estimates from studies that present their results in terms of standard deviations, we derive that the cognitive skill gap maps into hourly wage differences of, e.g., 16.8% (= $0.65*25.9\%$) for male and 22.2% for female high school graduates (Heckman, Stixrud, and Urzua, 2006) and a GPA difference of 23.1% of a standard deviation (Humphries and Kosse, 2017). The SES gap in patience maps into a 12.6% difference in the probability of underage drinking (Sutter et al., 2013) and into a 4.9% difference in disciplinary referrals in school (Castillo et al., 2011). The gap in risk-taking maps into a 4.5% difference in the probability of being a smoker (Dohmen et al., 2011). The SES gap in altruism maps into an about 5% difference in the probability to donate or volunteer (Falk et al., 2016).

mediating variables regarding the relationship between SES across generations. Third, our results suggest that fundamental characteristics of the utility function are not fixed or determined at birth, but rather endogenously formed through parental investments early in life, such that familial investments may have implications for utility maximization at later stages. Regarding the transferability of our results to theoretical and empirical models of economic choice, it is important that economic preferences were elicited by means of revealed preferences in incentivized experiments, which are commonly used to approximate the shape of the utility function.

In contrast to other studies, we use one coherent framework to study the gaps in IQ and key economic preferences and document that, at elementary school age, they all systematically differ by SES. Only such a comprehensive perspective can provide insights into the simultaneous determination of "risk factors" that are related to SES. This is important because economic preferences and IQ do typically not affect single decisions and life-outcomes in an isolated manner, but rather jointly (Heckman, Stixrud, and Urzua, 2006; Ida and Goto, 2009; Becker et al., 2012; Sutter et al., 2013). For example, one would expect that individuals who are at the same time risk-taking and impatient are more likely to engage in addictive behaviors such as smoking, drinking or gambling (Ida and Goto, 2009; Sutter et al., 2013). Our results document that, on average, children from families with lower SES are less patient *and* more risk-taking. Thus, they tend to combine characteristics that make them more vulnerable to addictive behaviors. Moreover, children from families with higher SES are more intelligent *and* more prosocial. In this regard, Deming (2017) shows pronounced employment and wage growth for jobs requiring the combination of high cognitive and high social skills. Regarding education attainment, the pattern of lower discount rates and more intelligence of children from high SES families makes it more likely for them to obtain higher levels of education. Altogether, systematic differences in a child's IQ and economic preferences by parental SES result in a tendency to favor social immobility.

Our results also deliver insights regarding the importance and functioning of parental investments. In line with previous studies (e.g., Guryan, Hurst, and Kearney, 2008; Cobb-Clark, Salamanca, and Zhu, 2016), we document that high SES families significantly outperform low SES families when it comes to both parenting style and time investments. Their day-to-day interactions with the child are more likely to be characterized by a warm and forthcoming parenting style and they spend a larger fraction of their time on stimulating activities. Interestingly, time investments are more strongly affected by parental education, while a positive parenting style is more strongly associated with household income. Both types of investments in turn are important for the development of IQ and economic preferences. In particular, risk-taking and patience are relatively strongly determined by time investments, while a positive parenting style and time matter similarly for the formation of IQ and altruism. Our results also indicate a large degree of substitutability between both types of investments and vis-à-vis maternal characteristics. This implies that even parents with, e.g., low levels of patience can improve their children's patience through investments and, even more so, since their overall investment productivity is no lower than for high SES families.

Finally, our results allow us to derive implications about the impact of policies that enhance socio-economic resources or parental investments, respectively. Congruent with the literature (Lindqvist and Vestman, 2011; Dahl and Lochner, 2012), we find that parental compulsory schooling or household income policies are relatively more effective in closing the SES gap in IQ, but less effective in altering the SES gaps in economic preferences. By contrast, policies that directly target investments are most effective in closing the SES gaps in economic preferences. Specifically, given our assumptions, a policy raising both parenting style and time investments among low SES families by 20% of a standard deviation would close roughly two-thirds of the gaps in patience and altruism, and it would fully close the SES gap in risk-taking. This finding is akin to literature showing that non-cognitive traits are often more easily malleable than cognitive traits in response to a change in early childhood investments (see, e.g., Heckman et al., 2010; Heckman, Pinto, and Savelyev, 2013), although these papers do not focus specifically on the development of economic preferences.

In future research, richer data on genetic, social, and other factors may help to uncover more precisely the mechanisms through which parental characteristics affect both SES, and child characteristics. Moreover, future work may ascertain whether early childhood interventions targeted at parental investments (such as Doyle et al., 2017) unveil effects on child economic preferences that are of a similar magnitude as those predicted in this study.

# References

Aisenbrey, Silke and Anette Fasang. 2017. "The interplay of work and family trajectories over the life course: Germany and the United States in comparison." *American Journal of Sociology* 122 (5):1448–1484.

Åkerlund, David, Bart H.H. Golsteyn, Hans Grönqvist, and Lena Lindahl. 2016. "Time Discounting and Criminal Behavior." *Proceedings of the National Academy of Sciences* 113 (22):6160–6165.

Aknin, Lara B., Christopher P. Barrington-Leigh, Elizabeth W. Dunn, John F. Helliwell, Justine Burns, Robert Biswas-Diener, Imelda Kemeza, Paul Nyende, Claire E. Ashton-James, and Michael I. Norton. 2013. "Prosocial Spending and Well-Being: Cross-Cultural Evidence for a Psychological Universal." *Journal of Personality and Social Psychology* 104 (4):635.

Alan, Sule, Nazli Baydar, Teodora Boneva, Thomas Crossley, and Seda Ertac. 2017. "Transmission of Risk Preferences from Mothers to Daughters." *Journal of Economic Behavior & Organization* 134:60–77.

Almås, Ingvild, Alexander W. Cappelen, Kjell G. Salvanes, Erik Sørensen, and Bertil Tungodden. 2016. "What Explains the Gender Gap in College Track Dropout? Experimental and Administrative Evidence." *American Economic Review* 106 (5):296–302.

Almlund, Mathilde, Angela L. Duckworth, James J. Heckman, and Tim D. Kautz. 2011. "Personality Psychology and Economics." In *Handbook of the Economics of Education*, vol. 4, edited by Eric A.Hanushek, Stephen Machin, and Ludger Woessmann. 1–181.

Anderson, Lisa R. and Jennifer M. Mellor. 2008. "Predicting Health Behaviors with an Experimental Measure of Risk Preference." *Journal of Health Economics* 27:1260–1274.

Angerer, Silvia, Daniela Glätzle-Rützler, Philipp Lergetporer, and Matthias Sutter. 2015a. "Donations, Risk Attitudes and Time Preferences: A study on Altruism in Primary School Children." *Journal of Economic Behavior & Organization* 115:67–74.

———. 2015b. "How to Measure Time Preferences in Children: A Comparison of Two Methods." *Journal of the Economic Science Association* 1:158–69.

Angrist, Joshua and Jörn-Steffen Pischke. 2009. *Mostly Harmless Econometrics: an Empiricists Guide*. Princeton: Princeton University Press.

Arrondel, Luc and Nicolas Frémeaux. 2016. "'For richer, for poorer': Assortative mating and savings preferences." *Economica* 83 (331):518–543.

Attanasio, Orazio, Sarah Cattan, Emla Fitzsimons, Costas Meghir, and Marta Rubio-Codina. 2015. "Estimating the Production Function for Human Capital: Results from a Randomized Control Trial in Colombia." National Bureau of Economic Research Working Paper No. 20965.

Baran, Nicole M., Paola Sapienza, and Luigi Zingales. 2010. "Can We Infer Social Preferences from the Lab? Evidence from the Trust Game." CEPR Discussion Paper No. 7634.

Baranov, Victoria, Sonia Bhalotra, Pietro Biroli, and Joanna Maselko. 2016. "Maternal Depression, Parental Investments and Early Child Development: Evidence from a Randomized Control Trial." Mimeo.

Barsky, Robert B., F. Thomas Juster, Miles S. Kimball, and Matthew D. Shapiro. 1997. "Preference Parameters and Behavioral Heterogeneity: An Experimental Approach in the Health and Retirement Study." *Quarterly Journal of Economics* 112 (2):537–579.

Bartlett, Maurice S. 1937. "The statistical conception of mental factors." *British journal of Psychology* 28 (1):97.

Bartling, Björn, Ernst Fehr, Barbara Fischer, Fabian Kosse, Michel Maréchal, Friedhelm Pfeiffer, Daniel Schunk, Jürgen Schupp, C. Katharina Spieß, and Gert G. Wagner. 2010. "Determinanten kindlicher Geduld – Ergebnisse einer Experimentalstudie im Haushaltskontext." *Journal of Applied Social Science Studies - Schmollers Jahrbuch* 130:297–323.

Bauer, Michal, Julie Chytilová, and Barbara Pertold-Gebicka. 2014. "Parental Background and Other-Regarding Preferences in Children." *Experimental Economics* 17:24–46.

Becker, Anke, Thomas Deckers, Thomas Dohmen, Armin Falk, and Fabian Kosse. 2012. "The Relationship Between Economic Preferences and Psychological Personality Measures." *Annual Review of Economics* 4 (1):453–478.

Becker, Gary S. and Nigel Tomes. 1986. "Human Capital and the Rise and Fall of Families." *Journal of Labor Economics* 4:1–39.

Belzil, Christian and Marco Leonardi. 2007. "Can Risk Aversion Explain Schooling Attainments? Evidence from Italy." *Labour Economics* 14 (6):957–970.

Ben-Porath, Yoram. 1967. "The Production of Human Capital and the Life-Cycle of Earnings." *Journal of Political Economy* 75 (4):352–365.

Benenson, Joyce F., Joanna Pascoe, and Nicola Radmore. 2007. "Children's Altruistic Behavior in the Dictator Game." *Evolution and Human Behavior* 28:168–175.

Berger, Kathleen. 2011. *The Developing Person Through the Lifespan.* Worth Publishers.

Bickel, Warren K., Amy L. Odum, and Gregory J. Madden. 1999. "Impulsivity and Cigarette Smoking: Delay Discounting in Current, Never, and Ex-Smokers." *Psychopharmacology* 146 (4):447–454.

Bisin, Alberto and Thierry Verdier. 2000. "Beyond the Melting Pot: Cultural Transmission, Marriage, and the Evolution of Ethnic and Religious Traits." *The Quarterly Journal of Economics* 115 (3):955–988.

———. 2001. "The Economics of Cultural Transmission and the Dynamics of Preferences." *Journal of Economic Theory* 97 (2):298–319.

Black, Sandra E., Paul J. Devereux, and Kjell G. Salvanes. 2009. "Like Father, Like Son? A Note on the Intergenerational Transmission of IQ Scores." *Economics Letters* 105:138–140.

Bonin, Holger, Thomas Dohmen, Armin Falk, David Huffman, and Uwe Sunde. 2007. "Cross-sectional earnings risk and occupational sorting: The role of risk attitudes." *Labour Economics* 14 (6):926–937.

Bono, Emilia Del, Marco Francesconi, Yvonne Kelly, and Amanda Sacker. 2016. "Early maternal time investment and early child outcomes." *The Economic Journal* 126 (596):F96–F135.

Borghans, Lex, Angela L. Duckworth, James J. Heckman, and Bas ter Weel. 2008. "The Economics and Psychology of Personality Traits." *Journal of Human Resources* 43 (4):972–1059.

Borghans, Lex and Bart H.H. Golsteyn. 2006. "Time Discounting and the Body Mass Index: Evidence from the Netherlands." *Economics and Human Biology* 4 (1):39–61.

Borghans, Lex, Bas ter Weel, and Bruce A. Weinberg. 2008. "Interpersonal Styles and Labor Market Outcomes." *The Journal of Human Resources* 43 (4):815–858.

Bowlby, John. 2008. *Attachment*. Basic books.

Bradley, Robert H. and Robert F. Corwyn. 2002. "Socioeconomic Status and Child Development." *Annual Review of Psychology* 53:371–399.

Burchinal, Margaret R., Joanne E. Roberts, Stephen Hooper, and Susan A. Zeisel. 2000. "Cumulative risk and early cognitive development: a comparison of statistical risk models." *Developmental Psychology* 36 (6):793.

Burks, Stephen V., Jeffrey P Carpenter, Lorenz Goette, and Aldo Rustichini. 2009. "Cognitive skills affect economic preferences, strategic behavior, and job attachment." *Proceedings of the National Academy of Sciences* 106 (19):7745–7750.

Burks, Stephen V., Connor Lewis, Paul A. Kivi, Amanda Wiener, Jon E. Anderson, Lorenz Götte, Colin G. DeYoung, and Aldo Rustichini. 2015. "Cognitive Skills, Personality, and Economic Preferences in Collegiate Success." *Journal of Economic Behavior & Organization* 115:30–44.

Burks, Stephen V., Daniele Nosenzo, Jon Anderson, Matthew Bombyk, Derek Ganzhorn, Lorenz Götte, and Aldo Rustichini. 2016. "Lab Measures of Other-Regarding Preferences Can Predict Some Related On-the-Job Behavior: Evidence from a Large Scale Field Experiment." IZA Discussion Paper No. 9767.

Burton, Peter, Shelley Phipps, and Lori Curtis. 2002. "All in the Family: A Simultaneous Model of Parenting Style and Child Conduct." *American Economic Review: Papers and Proceedings* 92:368–372.

Cadena, Bryan C. and Benjamin J. Keys. 2015. "Human Capital and the Lifetime Costs of Impatience." *American Economic Journal: Economic Policy* 7 (3):126–153.

Caliendo, Marco, Frank Fossen, and Alexander Kritikos. 2010. "The Impact of Risk Attitudes on Entrepreneurial Survival." *Journal of Economic Behavior & Organization* 76 (1):45–63.

Carneiro, Pedro, Karsten T Hansen, and James J Heckman. 2003. "2001 Lawrence R. Klein Lecture Estimating Distributions of Treatment Effects with an Application to the Returns to Schooling and Measurement of the Effects of Uncertainty on College Choice." *International Economic Review* 44 (2):361–422.

Carneiro, Pedro, James J. Heckman, and Dimitriy V. Masterov. 2005. "Labor Market Discrimination and Racial Differences in Premarket Factors." *The Journal of Law and Economics* 48 (1):1–39.

Carpenter, Jeffrey and Erika Seki. 2011. "Do Social Preferences Increase Productivity? Field Experimental Evidence from Fishermen in Toyama Bay." *Economic Inquiry* 49 (2):612–630.

Case, Anne, Darren Lubotsky, and Christina Paxson. 2002. "Economic Status and Health in Childhood: The Origins of the Gradient." *American Economic Review* 92:1308–1334.

Caspi, Avshalom. 2000. "The Child is the Father of the Man: Personality Continuities From Childhood to Adulthood." *Journal of Personality and Social Psychology* 78 (1):158–172.

Caspi, Avshalom, HonaLee Harrington, Barry Milne, James W. Amen, Reremoana F. Theodore, and Terrie E. Moffitt. 2003. "Children's Behavioral Styles at Age 3 are Linked to Their Adult Personality Traits at Age 26." *Journal of Personality* 71 (4):495–513.

Castillo, Marco, Paul J. Ferraro, Jeffrey L. Jordan, and Ragan Petrie. 2011. "The Today and Tomorrow of Kids: Time Preferences and Educational Outcomes of Children." *Journal of Public Economics* 95:1377–1385.

Castillo, Marco, Jeffrey L. Jordan, and Ragan Petrie. 2015. "How much is Patience Worth? Discount Rates of Children and High School Completion." Mimeo.

Cattell, Raymond B. 1971. *Abilities: Their Structure, Growth, and Action.* New York: Houghton Mifflin.

Cawley, John, James J. Heckman, and Edward Vytlacil. 2001. "Three Observations on Wages and Measured Cognitive Ability." *Labor Economics* 8:419–442.

Chabris, Christopher F., David Laibson, Carrie L. Morris, Jonathon P. Schuldt, and Dmitry Taubinsky. 2008. "Individual Laboratory-Measured Discount Rates Predict Field Behavior." *Journal of Risk and Uncertainty* 37 (2):237–269.

Charness, Gary, Uri Gneezy, and Alex Imas. 2013. "Experimental Methods: Eliciting Risk Preferences." *Journal of Economic Behavior and Organization* 87:43–51.

Chuang, Yating and Laura Schechter. 2015. "Stability of Experimental and Survey Measures of Risk, Time, and Social Preferences: A Review and Some New Results." *Journal of Development Economics* 117:151–170.

Cobb-Clark, Deborah A., Nicolas Salamanca, and Anna Zhu. 2016. "Parenting Style as an Investment in Human Development." IZA Discussion Paper No. 9686.

Cunha, Flavio and James J. Heckman. 2007. "The Technology of Skill Formation." *American Economic Review* 97 (2):31–47.

Cunha, Flavio, James J. Heckman, and Susanne M. Schennach. 2010. "Estimating the Technology of Cognitive and Noncognitive Skill Formation." *Econometrica* 78 (3):883–931.

Dahl, Gordon B. and Lance Lochner. 2012. "The Impact of Family Income on Child Achievement: Evidence from the Earned Income Tax Credit." *The American Economic Review* 102 (5):1927–1956.

Dawson, Chris and Andres Henley. 2015. "Gender, Risk and Venture Creation Intentions." *Journal of Small Business Management* 53 (2):501–515.

Delaney, Liam and Orla Doyle. 2012. "Socioeconomic Differences in Early Childhood Time Preferences." *Journal of Economic Psychology* 33:237–247.

Delaney, Liam, Colm Harmonb, and Martin Ryanc. 2013. "The Role of Noncognitive Traits in Undergraduate Study Behaviours." *Economics of Education Review* 32:181–195.

DellaVigna, Stefano and M. Daniele Paserman. 2005. "Job Search and Impatience." *Journal of Labor Economics* 23 (3):527–588.

Deming, David J. 2017. "The Growing Importance of Social Skills in the Labor Market." *Quarterly Journal of Economics,* 132 (4):1593–1640.

Doepke, Matthias and Fabrizio Zilibotti. 2017. "Parenting with Style: Altruism and Paternalism in Intergenerational Preference Transmission." *Econometrica* 85 (5):1331–1371.

———. 2019. *Love, Money, and Parenting: How Economics Explains the Way We Raise Our Kids.* Princeton University Press.

Dohmen, Thomas, Benjamin Enke, Armin Falk, David Huffman, and Uwe Sunde. 2018. "Patience and Comparative Development." Working Paper.

Dohmen, Thomas and Armin Falk. 2011. "Performance Pay and Multi-Dimensional Sorting - Productivity, Preferences and Gender." *American Economic Review* 101 (2):556–590.

Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde. 2009. "Homo Reciprocans: Survey Evidence on Behavioural Outcomes." *Economic Journal* 119 (536):592–612.

———. 2010. “Are Risk Aversion and Impatience Related to Cognitive Ability?” *American Economic Review* 100 (3):1238–1260.

———. 2012. “The Intergenerational Transmission of Risk and Trust Attitudes.” *Review of Economic Studies* 79 (2):645–677.

Dohmen, Thomas, Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, and Gert G. Wagner. 2011. “Individual Risk Attitudes: Measurement, Determinants and Behavioral Consequences.” *Journal of the European Economic Association* 9 (3):522–550.

Doyle, Orla, Colm Harmon, James J. Heckman, Caitriona Logue, and Seong Hyeok Moon. 2017. “Early Skill Formation and the Efficiency of Parental Investment: A Randomized Controlled Trial of Home Visiting.” *Labour Economics* 45:40–58.

Duncan, Greg J. and Katherine Magnuson. 2013. “Investing in Preschool Programs.” *The Journal of Economic Perspectives* 27 (2):109–132.

Dunn, Douglas M. and Lloyd M. Dunn. 2007. *Peabody Picture Vocabulary Test, Manual.* Minneapolis MN: NCS Pearson, Inc, 4 ed.

Eckel, Catherine, Cathleen Johnson, and Claude Montmarquette. 2005. “Saving Decisions of the Working Poor: Short- and Long-Term Horizons.” In *Field Experiments in Economics (Research in Experimental Economics)*, vol. 10, edited by Glenn W. Harrison, Jeffrey Carpenter, and John A. List. Emerald Group Publishing Limited, 219 – 260.

Eika, Lasse, Magne Mogstad, and Basit Zafar. 2019. “Educational Assortative Mating and Household Income Inequality.” *Journal of Political Economy* forthcoming.

Eisenberg, Nancy, Tracy L. Spinrad, and Ariel Knafo-Noam. 2015. *Handbook of Child Psychology and Developmental Science: Socioemotional Processes*, chap. Prosocial development. 610–656.

Falk, Armin, Anke Becker, Thomas Dohmen, Benjamin Enke, David Huffman, and Uwe Sunde. 2018. “Global Evidence on Economic Preferences.” *The Quarterly Journal of Economics* 133 (4):1645–1692.

Falk, Armin, Anke Becker, Thomas Dohmen, David Huffman, and Uwe Sunde. 2016. “The Preference Survey Module: A Validated Instrument for Measuring Risk, Time, and Social Preferences.” IZA Discussion Paper No. 9674.

Falk, Armin and Fabian Kosse. 2016. “Early Childhood Environment, Breastfeeding and the Formation of Preferences.” HCEO Working Paper 2016-036.

Fehr, Ernst, Helen Bernhard, and Bettina Rockenbach. 2008. “Egalitarianism in Young Children.” *Nature* 454:1079–1084.

Fehr, Ernst, Daniela Rützler, and Matthias Sutter. 2013. “The Development of Egalitarianism, Altruism, Spite and Parochialism in Childhood and Adolescence.” *European Economic Review* 64:369–383.

Francesconi, Marco, Stephen P. Jenkins, and Thomas Siedler. 2010. "Childhood family structure and schooling outcomes: evidence for Germany." *Journal of Population Economics* 23 (3):1073–1103.

Fuchs, Victor. 1982. "Time Preference and Health: An Exploratory Study." In *Economic Aspects of Health*, edited by Victor Fuchs. University of Chicago Press, 93–120.

Ganzeboom, Harry B.G., Paul M. De Graaf, and Donald J. Treiman. 1992. "A Standard International Socio-economic Index of Occupational Status." *Social Science Research* 21 (1):1–56.

Gensowski, Miriam. 2014. "Personality, IQ, and Lifetime Earnings." IZA Discussion Paper No. 8235.

Gerlitz, Jean-Yves and Jürgen Schupp. 2005. "Zur Erhebung der Big-Five-basierten Persönlichkeitsmerkmale im SOEP." *DIW Berlin, Research Notes* 4.

Gertler, Paul, James J. Heckman, Rodrigo Pinto, Arianna Zanolini, Christel Vermeersch, Susan Walker, Susan M. Chang, and Sally Grantham-McGregor. 2014. "Labor Market Returns to an Early Childhood Stimulation Intervention in Jamaica." *Science* 344 (6187):998–1001.

Golsteyn, Bart H.H., Hans Grönqvist, and Lena Lindahl. 2014. "Adolescent Time Preferences Predict Lifetime Outcomes." *Economic Journal* 124:F739–F761.

Groves, Melissa O. 2005. "How Important Is Your Personality? Labor Market Returns to Personality for Women in the US and UK." *Journal of Economic Psychology* 26 (6):827–841.

Guiso, Luigi and Monica Paiella. 2008. "Risk Aversion, Wealth, and Background Risk." *Journal of the European Economic Association* 6 (6):1109–1150.

Guryan, Jonathan, Erik Hurst, and Melissa Kearney. 2008. "Parental Education and Parental Time with Children." *The Journal of Economic Perspectives* 22 (3):23–46.

Hagenaars, Aldi J.M., Klaas De Vos, and Asghar Zaidi. 1994. "Poverty Statistics in the Late 1980s: Research Based on Micro-Data." Tech. rep., Study carried out for Eurostat, Office for Official Publications of the European Community, Luxembourg.

Hanushek, Eric A. 2010. "How Well Do We Understand Achievement Gaps?" *Focus* 27 (2):5–12.

Hanushek, Eric A. and Ludger Woessmann. 2008. "The Role of Cognitive Skills in Economic Development." *Journal of Economic Literature* 46 (3):607–668.

Harrison, Glenn W., Morten I. Lau, and E. Elisabet Rutström. 2010. "Individual Discount Rates and Smoking: Evidence from a Field Experiment in Denmark." *Journal of Health Economics* 29 (5):708–717.

Heckman, James J. 2007. "The Economics, Technology, and Neuroscience of Human Capability Formation." *Proceedings of the National Academy of Sciences* 104 (33):13250–13255.

Heckman, James J. 2008. "Schools, Skills, and Synapses." *Economic Inquiry* 46 (3):289–324.

Heckman, James J. 2011. "The Economics of Inequality: The Value of Early Childhood Education." *American Educator* 35 (1):31.

Heckman, James J., Margaret L. Holland, Kevin K. Makino, Rodrigo Pinto, and Maria Rosales-Rueda. 2017. "An Analysis of the Memphis Nurse-Family Partnership Program." National Bureau of Economic Research Working Paper No. 23610.

Heckman, James J., Seong Hyeok Moon, Rodrigo Pinto, Peter A. Savelyev, and Adam Yavitz. 2010. "The Rate of Return to the High Scope Perry Preschool Program." *Journal of Public Economics* 94 (1):114–128.

Heckman, James J. and Stefano Mosso. 2014. "The Economics of Human Development and Social Mobility." *Annual Review of Economics* 6 (1):689–733.

Heckman, James J., Rodrigo Pinto, and Peter Savelyev. 2013. "Understanding the Mechanisms through which an Influential Early Childhood Program Boosted Adult Outcomes." *The American Economic Review* 103 (6):2052–2086.

Heckman, James J., Jora Stixrud, and Sergio Urzua. 2006. "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior." *Journal of Labor Economics* 24 (3):411–482.

Heckman, James J. and Edward Vytlacil. 2001. "Identifying the Role of Cognitive Ability in Explaining the Level of and Change in the Return to Schooling." *Review of Economics and Statistics* 83 (1):1–12.

Heineck, Guido and Silke Anger. 2010. "The Returns to Cognitive Abilities and Personality Traits in Germany." *Labour Economics* 17 (3):535–546.

Holbein, John B. 2017. "Childhood Skill Development and Adult Political Participation." *American Political Science Review* 111 (3):572–583.

Holt, Charles A. and Susan K. Laury. 2002. "Risk Aversion and Incentive Effects." *The American Economic Review* 92 (5):1644–1655.

Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein. 2004. "Social Interaction and Stock-Market Participation." *The Journal of Finance* 59:137–163.

Hsieh, Chihmao, Simon C. Parker, and C. Mirjam van Praag. 2017. "Risk, Balanced Skills and Entrepreneurship." *Small Business Economics* 48 (2):287–302.

Hsin, Amy and Christina Felfe. 2014. "When Does Time Matter? Maternal Employment, Children's Time with Parents, and Child Development." *Demography* 51 (5):1867–1894.

Hübner, Malte and Gonzague Vannoorenberghe. 2015. "Patience and Long-Run Growth." *Economics Letters* 137:163–167.

Hufe, Paul and Andreas Peichl. 2016. "Beyond Equal Rights: Equality of Opportunity in Political Participation." ZEW Discussion Paper 16-068.

Humphries, John E. and Fabian Kosse. 2017. "On the Interpretation of Non-Cognitive Skills - What is Being Measured and Why it Matters." *Journal of Economic Behavior & Organization* 136:174–185.

Ida, Takanori and Rei Goto. 2009. "Interdependency among Addictive Behaviours and Time/Risk Preferences: Discrete Choice Model Analysis of Smoking, Drinking, and Gambling." *Journal of Economic Psychology* 30 (4):608–621.

Inhelder, Bärbel and Jean Piaget. 1958. *The Growth of Logical Thinking from Childhood to Adolescence: An Essay on the Construction of Formal Operational Structures.* Routledge and Kegan Paul Ltd.

Jaeger, David A., Thomas Dohmen, Armin Falk, David Huffman, Uwe Sunde, and Holger Bonin. 2010. "Direct Evidence on Risk Attitudes and Migration." *The Review of Economics and Statistics* 92 (3):684–689.

Jencks, Christopher and Meredith Phillips. 1998. *The Black-White Test Score Gap.* Washington, D.C.: Brookings Institution Press.

Karlan, Dean S. 2005. "Using Experimental Economics to Measure Social Capital and Predict Financial Decisions." *The American Economic Review* 95 (5):1688–1699.

Kimball, Miles S., Claudia R. Sahm, and Matthew D. Shapiro. 2008. "Imputing Risk Tolerance From Survey Responses." *Journal of the American Statistical Association* 103 (483):1028–1038.

Kimball, Miles S, Claudia R Sahm, and Matthew D Shapiro. 2009. "Risk preferences in the PSID: Individual imputations and family covariation." *American Economic Review* 99 (2):363–68.

Kirby, Kris N. and Nancy M. Petry. 2004. "Heroin and Cocaine Abusers Have Higher Discount Rates for Delayed Rewards than Alcoholics or Non-Drug-Using Controls." *Addiction* 99 (4):461–471.

Kirby, Krix N., Nancy M. Petry, and Warren K. Bickel. 1999. "Heroin Addicts Have Higher Discount Rates for Delayed Rewards Than Non-Drug-Using Controls." *Journal of Experimental Psychology General* 128 (1):78–87.

Kolenikov, Stanislav. 2010. "Resampling Variance Estimation for Complex Survey Data." *Stata Journal* 10 (2):165–199.

Kosfeld, Michael and Devesh Rustagi. 2015. "Leader Punishment and Cooperation in Groups: Experimental Field Evidence from Commons Management in Ethiopia." *American Economic Review* 105 (2):747–783.

Kosse, Fabian, Pinger Pia Deckers, Thomas, Hannah Schildberg-Hörisch, and Armin Falk. 2019. "The Formation of Prosociality: Causal Evidence on the Role of Social Environment." *Journal of Political Economy,* forthcoming.

Kosse, Fabian and Friedhelm Pfeiffer. 2012. "Impatience among Preschool Children and their Mothers." *Economics Letters* 115 (3):493–495.

———. 2013. "Quasi-hyperbolic time preferences and their intergenerational transmission." *Applied Economics Letters* 20 (10):983–986.

Leibbrandt, Andreas. 2012. "Are Social Preferences Related to Market Performance?" *Experimental Economics* 15 (4):589–603.

Lindqvist, Erik and Roine Vestman. 2011. "The Labor Market Returns to Cognitive and Noncognitive Ability: Evidence from the Swedish Enlistment." *American Economic Journal: Applied Economics* 3 (1):101–128.

Mascie-Taylor, CG Nicholas and Steven G Vandenberg. 1988. "Assortative mating for IQ and personality due to propinquity and personal preference." *Behavior Genetics* 18 (3):339–345.

McEwan, Patrick J. 2015. "Improving Learning in Primary Schools of Developing Countries: A Meta-Analysis of Randomized Experiments." *Review of Educational Research* 85 (3):353–394.

McLanahan, Sara. 2009. "Fragile families and the reproduction of poverty." *The Annals of the American Academy of Political and Social Science* 621 (1):111–131.

Meier, Stephan and Charles Sprenger. 2010. "Present-Biased Preferences and Credit Card Borrowing." *American Economic Journal: Applied Economics* 2 (1):193–210.

Mischel, Walter, Yuichi Shoda, and Monica L. Rodriguez. 1989. "Delay of Gratification in Children." *Science* 244 (4907):933–938.

Moffitt, Terrie E., Louise Arseneault, Daniel Belsky, Nigel Dickson, Robert J. Hancox, HonaLee Harrington, Renate Houts, Richie Poulton, Brent W. Roberts, Stephen Ross, Malcolm R. Sears, W. Murray Thomson, and Avshalom Caspi. 2011. "A Gradient of Childhood Self-Control Predicts Health, Wealth, and Public Safety." *Proceedings of the National Academy of Sciences* 108 (7):2693–2698.

Obradović, Jelena, Nicole R. Bush, Juliet Stamperdahl, Nancy E. Adler, and W. Thomas Boyce. 2010. "Biological sensitivity to context: The interactive effects of stress reactivity and family adversity on socioemotional behavior and school readiness." *Child Development* 81 (1):270–289.

Oreopoulos, Philip, Marianne E. Page, and Ann Huff Stevens. 2006. "The Intergenerational Effects of Compulsory Schooling." *Journal of Labor Economics* 24 (4):729–760.

Petermann, Franz and Ulrike Petermann. 2010. *HAWIK–IV: Hamburg-Wechsler-Intelligenztest für Kinder – IV.* Bern: Huber.

Piatek, Rémi and Pia Pinger. 2016. "Maintaining (locus of) control? Data combination for the identification and inference of factor structure models." *Journal of Applied Econometrics* 31 (4):734–755.

Price, Joseph. 2008. "Parent-Child Quality Time does Birth Order Matter?" *Journal of Human Resources* 43 (1):240–265.

Reynolds, Arthur J., Judy A. Temple, and Suh-Ruu Ou. 2010. "Preschool Education, Educational Attainment, and Crime Prevention: Contributions of Cognitive and Non-Cognitive Skills." *Children and Youth Services Review* 32 (8):1054–1063.

Roberts, Brent W. and Wendy F. DelVecchio. 2000. "The Rank-Order Consistency of Personality Traits From Childhood to Old Age: A Quantitative Review of Longitudinal Studies." *Psychological Bulletin* 126 (1):3–25.

Rogoff, Barbara. 1990. *Apprenticeship in thinking: Cognitive development in social context.* Oxford university press.

Rustagi, Devesh, Stefanie Engel, and Michael Kosfeld. 2010. "Conditional Cooperation and Costly Monitoring Explain Success in Forest Commons Management." *Science* 330 (6006):961–965.

Rustichini, Aldo, Colin G. DeYoung, Jon Anderson, and Stephen V. Burks. 2016. "Toward the Integration of Personality Theory and Decision Theory in the Explanation of Economic and Health Behavior." *Journal of Behavioral and Experimental Economics* 64:122–137.

Sarzosa, Miguel and Sergio Urzúa. 2015. "Implementing Factor Models for Unobserved Heterogeneity in Stata: The `heterofactor` Command." Working Paper, Purdue University.

———. 2016. "Implementing Factor Models for Unobserved Heterogeneity in Stata." *Stata Journal* 16 (1):197–228.

Schmidt, Frank L. and John E. Hunter. 2004. "General Mental Ability in the World of Work: Occupational Attainment and Job Performance." *Journal of Personality and Social Psychology* 86 (1):162–73.

Shoda, Yuichi, Walter Mischel, and Philip K. Peake. 1990. "Predicting Adolescent Cognitive and Self-Regulatory Competencies from Preschool Delay of Gratification: Identifying Diagnostic Conditions." *Developmental Psychology* 26 (6):978–986.

Skinner, Burrhus Frederic. 1953. *Science and Human Behavior*. Macmillan, New York.

Slovic, Paul. 1966. "Risk-Taking in Children: Age and Sex Differences." *Child Development* 37 (1):169–176.

SOEP. 2010. "German Socio-Economic Panel, Data for Years 1984-2009, Version 26." doi:10.5684/soep.v26. Dataset.

———. 2017. “German Socio-Economic Panel, Data for Years 1984-2016, Version 33.1.” doi: 10.5684/soep.v33.1. Dataset.

Strenze, Tarmo. 2007. “Intelligence and Socioeconomic Success: A Meta-Analytic Review of Longitudinal Research.” *Intelligence* 35:401–426.

Sutter, Matthias, Martin G. Kocher, Daniela Rützler, and Stefan T. Trautmann. 2013. “Impatience and Uncertainty: Experimental Decisions Predict Adolescents’ Field Behavior.” *American Economic Review* 103 (1):510–531.

Thönnissen, Carolin, Barbara Wilhelm, Stefan Fiedrich, Philipp Alt, and Sabine Walper. 2015. “Scales Manual of the German Family Panel, Release 6.0.” Tech. rep.

Ventura, Luigi. 2003. “Direct Measures of Time Preferences.” *The Economic and Social Review* 34 (3):293–310.

Vischer, Thomas, Thomas Dohmen, Armin Falk, David Huffman, Jürgen Schupp, Uwe Sunde, and Gert G. Wagner. 2013. “Validating an Ultra-Short Survey Measure of Patience.” *Economics Letters* 120 (2):142–145.

von Gaudecker, Hans-Martin, Arthur van Soest, and Erik Wengström. 2011. “Heterogeneity in Risky Choice Behavior in a Broad Population.” *The American Economic Review* 101 (2):664–694.

Wagner, Gert G., Joachim Frick, and Jürgen Schupp. 2007. “The German Socio-Economic Panel Study (SOEP) – Evolution, Scope and Enhancements.” SOEPpapers No. 1.

Weinberg, Bruce A. 2001. “An Incentive Model of the Effect of Parental Income on Children.” *Journal of Political Economy* 109 (2):266–280.

Woessmann, Ludger. 2015. “An international look at the single-parent family; family structure matters more for US students.” *Education Next* 15 (2):42–50.

# A Appendix

## A.1 Literature

Table A1: IQ, economic preferences and life outcomes

| Paper | Data set | Outcomes | Results | IQ | Time preferences | Risk preferences | Social preferences |
|---|---|---|---|---|---|---|---|
| Åkerlund et al. (2016) | SBC, Adm. data | Crime | ■ | ● | ● | ○ | ○ |
| Almås et al. (2016) | Private | Education | ▣ | ◐ | ● | ● | ○ |
| Anderson and Mellor (2008) | Private | Health | ■ | ○ | ○ | ● | ○ |
| Baran, Sapienza, and Zingales (2010) | TCMLS | Donations | ■ | ○ | ○ | ○ | ● |
| Barsky et al. (1997) | HRS | Health, Personal Finance | ■ | ○ | ○ | ● | ○ |
| Becker et al. (2012) | GSOEP | Educ., Labor Market, Health, Satisf. | ■ | ○ | ● | ● | ● |
| Belzil and Leonardi (2007) | SHIW | Education | ■ | ○ | ○ | ● | ○ |
| Bickel, Odum, and Madden (1999) | Private | Health | ■ | ○ | ● | ○ | ○ |
| Bonin et al. (2007) | GSOEP | Labor Market | ■ | ○ | ○ | ● | ○ |
| Borghans and Golsteyn (2006) | DNB | Health | ▣ | ○ | ● | ○ | ○ |
| Borghans et al. (2008*b*) | BSS, BCS, BIBB | Labor Market | ▣ | ○ | ○ | ○ | ◐ |
| Burks et al. (2015) | Private | Education | ▣ | ● | ● | ● | ◐ |
| Burks et al. (2016) | Private | Labor Market | ■ | ○ | ○ | ○ | ● |
| Cadena and Keys (2015) | NLSY | Education, Labor Market, Health | ■ | ○ | ● | ○ | ○ |
| Caliendo, Fossen, and Kritikos (2010) | GSOEP | Labor Market | ■ | ○ | ○ | ● | ○ |
| Castillo et al. (2011) | Private | Education | ■ | ○ | ● | ○ | ○ |
| Castillo, Jordan, and Petrie (2015) | Private | Education | ■ | ○ | ● | ○ | ○ |
| Carpenter and Seki (2011) | Private | Labor Market | ■ | ○ | ○ | ○ | ● |
| Cawley, Heckman, and Vytlacil (2001) | NLSY | Labor Market | ■ | ● | ○ | ○ | ○ |
| Chabris et al. (2008) | Private | Health, Pers. Finance | ▣ | ○ | ● | ○ | ○ |
| Dawson and Henley (2015) | Private | Labor Market | ■ | ○ | ○ | ● | ○ |
| Deming (2017) | NLSY79, NLSY97 | Labor Market | ■ | ◐ | ○ | ○ | ◐ |
| Delaney, Harmonb, and Ryanc (2013) | IUS | Education | ▣ | ○ | ● | ● | ○ |
| DellaVigna and Paserman (2005) | PSID, NLSY | Labor Market | ■ | ○ | ● | ○ | ○ |
| Dohmen et al. (2009) | GSOEP | Labor Market | ■ | ○ | ○ | ○ | ● |
| Dohmen et al. (2011) | GSOEP | Labor Market, Health, Pers. Finance | ■ | ○ | ○ | ● | ○ |
| Dohmen and Falk (2011) | Private | Labor Market | ■ | ○ | ○ | ● | ○ |
| Dohmen et al. (2018) | Private | Development, Growth | ■ | ○ | ● | ○ | ○ |
| Eckel, Johnson, and Montmarquette (2005) | Private | Personal Finance | ▣ | ○ | ● | ● | ○ |
| Falk et al. (2018) | GPS | Education, Labor Market, Health | ■ | ● | ● | ● | ● |
| ctd. | | Personal Finance, Social Interaction | | | | | |
| Fuchs (1982) | Private | Education, Health | ■ | ○ | ● | ○ | ○ |
| Gensowski (2014) | Terman | Education, Labor Market | ■ | ● | ○ | ○ | ○ |
| Golsteyn, Grönqvist, and Lindahl (2014) | SBC | Education, Labor Market, Health | ■ | ○ | ● | ○ | ○ |
| Groves (2005) | NLSW, NCDS | Labor Market | ■ | ● | ○ | ○ | ◐ |
| Guiso and Paiella (2008) | SHIW | Educ., Labor M., Health, Pers. Fin. | ▣ | ○ | ○ | ● | ○ |
| Hanushek and Woessmann (2008) | Multiple | Labor Market | ■ | ◐ | ○ | ○ | ○ |
| Harrison, Lau, and Rutström (2010) | Private | Health | ■ | ○ | ● | ● | ○ |
| Heckman and Vytlacil (2001) | NLSY | Education, Labor Market | ■ | ◐ | ○ | ○ | ○ |
| Heckman, Stixrud, and Urzua (2006) | NLSY79 | Labor Market, Education, Health | ■ | ◐ | ○ | ○ | ○ |
| Heckman, Pinto, and Savelyev (2013) | Perry | Education, Labor Market, Health | ■ | ● | ○ | ○ | ○ |

*Continued on next page*

Table A1 – *Continued from previous page*

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Heineck and Anger (2010) | GSOEP | Labor Market | □ | ● | ○ | ○ | ◍ |
| Hong, Kubik, and Stein (2004) | HRS | Personal Finance | ■ | ○ | ○ | ● | ○ |
| Hsieh, Parker, and van Praag (2017) | Private | Labor Market | ■ | ○ | ○ | ● | ○ |
| Humphries and Kosse (2017) | GSOEP | Education | □ | ● | ● | ● | ○ |
| Jaeger et al. (2010) | GSOEP | Labor Market, Migration | ■ | ○ | ○ | ● | ○ |
| Karlan (2005) | Private | Personal Finance | ■ | ○ | ○ | ○ | ● |
| Kimball, Sahm, and Shapiro (2008) | HRS | Personal Finance | ■ | ○ | ○ | ● | ○ |
| Kirby, Petry, and Bickel (1999) | Private | Health | ■ | ○ | ● | ○ | ○ |
| Kirby and Petry (2004) | Private | Health | □ | ○ | ● | ○ | ○ |
| Kosfeld and Rustagi (2015) | Private | Labor Market | ■ | ○ | ○ | ○ | ● |
| Leibbrandt (2012) | Private | Performance in Open-Air Markets | ■ | ○ | ○ | ○ | ● |
| Meier and Sprenger (2010) | Private | Personal Finance | □ | ○ | ● | ○ | ○ |
| Mischel, Shoda, and Rodriguez (1989) | Private | Education | ■ | ○ | ● | ○ | ○ |
| Reynolds, Temple, and Ou (2010) | CLS | Education | ■ | ◍ | ○ | ○ | ◍ |
| Rustagi, Engel, and Kosfeld (2010) | Private | Labor Market | ■ | ○ | ○ | ○ | ● |
| Rustichini et al. (2016) | Private | Labor Market, Health, Pers. Finance | □ | ● | ● | ● | ○ |
| Schmidt and Hunter (2004) | Multiple | Labor Market | ■ | ● | ○ | ○ | ○ |
| Strenze (2007) | Multiple | Education, Labor Market | ■ | ● | ○ | ○ | ○ |
| Sutter et al. (2013) | Private | Education, Health, Pers. Finance | ■ | ○ | ● | ● | ○ |
| Ventura (2003) | SHIW | Health, Personal Finance | □ | ○ | ● | ○ | ○ |

**Notes**: Table shows papers that demonstrate the role of IQ, time preferences, risk preferences, social preferences for outcomes. ■ – Significant effects. □ – Mixed effects. ● - Used. ◍ – Somewhat used. ○ – Not used. Data sets: AddHealth– The National Longitudinal Study of Adolescent to Adult Health, BIBB-IAB data– Data of the Bundesinstitut für Berufsbildung and the Institute for Employment Research, BCS– British Cohort Study, BSS– British Skills Survey, GSOEP– German Socio-Economic Panel, CLS– Chicago Longitudinal Study, DNB– DNB Household Survey, GPS– Global Preferences Survey, HILDA– Household Income and Labour Dynamics in Australia, HRS– Health and Retirement Survey, IUS– Irish University Study, NELS– National Education Longitudinal Study of 1988, NLSW– National Longitudinal Survey of Young Women, NLSY– The National Longitudinal Survey of Youth, NLSY79– The National Longitudinal Survey of Youth 1979, NLSY97– National Longitudinal Survey of Youth 1997, NLS-72– National Longitudinal Study of the High School Class of 72, Perry– Perry Preschool Project, PSID– Panel Survey of Income Dynamics, SBC– Stockholm Birth Cohort Study, SHIW– Bank of Italy Survey of Household Income and Wealth, TCMLS– Templeton-Chicago MBA Longitudinal Study, Terman– Survey by Lewis Terman started at Stanford in 1921/22.

## A.2 Additional tables

Table A2: SES gaps in IQ, patience, risk-taking, and altruism

| | IQ | Patience | Risk-taking | Altruism |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low SES | −0.647 | −0.348 | 0.226 | −0.212 |
| Standard errors: | | | | |
| *a. Bootstrapped SE* | (0.091 )*** | (0.140 )** | (0.124 )* | (0.096 )** |
| *b. OLS/OIM SE* | (0.091 )*** | (0.134 )*** | (0.126 )* | (0.096 )** |
| *c. Huber-White SE* | (0.091 )*** | (0.135 )** | (0.127 )* | (0.094 )** |
| Observations | 435 | 435 | 435 | 435 |

**Notes**: The table shows coefficients of regressions, in which IQ or economic preferences are regressed on a low SES dummy that equals 1 for low and 0 for high SES families. Columns (1) and (4) are estimated using OLS. In columns (2) and (3), we take the censoring of the respective dependent variables into account and use Tobit. Standard errors are displayed in parentheses. We report three alternative estimates of standard errors: bootstrapped standard errors (1000 bootstrap replications) in line a., OLS standard errors (column (1) and (4)) and observed information matrix (OIM) standard errors for the Tobit models (column (2) and (3)) in line b., and Huber-White standard errors in line c. Significance at * p $<$ 0.1, ** p $<$ 0.05, *** p $<$ 0.01.

Table A3: IQ/economic preferences and teenage life outcomes

| | Success in school | Social participation | Juvenile offending |
|---|---|---|---|
| Panel A: Low SES | −0.174*** | −0.124** | 0.057 |
| Panel B: raw correlations | | | |
| IQ | 0.303*** | 0.136** | −0.022 |
| Patience | 0.110** | 0.110** | −0.057 |
| Risk-taking | −0.164*** | −0.032 | 0.199*** |
| Altruism | 0.156*** | −0.010 | −0.132** |
| Panel C: correlations cond. on SES | | | |
| IQ | 0.274*** | 0.107* | −0.006 |
| Patience | 0.092* | 0.097* | −0.052 |
| Risk-taking | −0.156*** | −0.029 | 0.197*** |
| Altruism | 0.141*** | −0.022 | −0.128** |

**Notes**: Panel A and B: Displayed correlations are Pearson correlation coefficients. Panel C: Displayed coefficients are standardized beta coefficients of an OLS regression (equivalent to Pearson correlation coefficients) where the respective standardized outcome is regressed on the respective standardized measure of the child and a low SES dummy. Success in school is measured by grade point average (converted such that higher grades are better). Social participation and juvenile offending are survey measures. For details see Section B.5. $N$(Success in school) = 344, $N$(Social participation) = 347 and $N$(Juvenile offending) = 348, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Gender gaps in IQ, patience, risk-taking, and altruism and SES gaps by gender

| | **IQ** | | **Patience** | | **Risk-taking** | | **Altruism** | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Male | 0.097 | 0.119 | 0.576*** | 0.536*** | 0.527*** | 0.339** | −0.393*** | −0.483*** |
| | (0.090) | (0.138) | (0.132) | (0.138) | (0.129) | (0.135) | (0.095) | (0.123) |
| Low SES | −0.646*** | −0.626*** | −0.351** | −0.104 | 0.228* | 0.095 | −0.214** | −0.299** |
| | (0.091) | (0.139) | (0.137) | (0.142) | (0.120) | (0.132) | (0.094) | (0.128) |
| Male x low SES | | −0.040 | | −0.260 | | 0.094 | | 0.163 |
| | | (0.181) | | (0.198) | | (0.181) | | (0.185) |
| Observations | 435 | 435 | 435 | 435 | 435 | 435 | 435 | 435 |

**Notes**: In columns (1), (3), (5) and (7), the table shows coefficients of regressions, in which IQ or economic preferences are regressed on a male dummy (1 for boys, 0 for girls) and a low SES dummy that equals 1 for low and 0 for high SES families. Columns (1) and (7) are estimated using OLS. In columns (3) and (5), we take the censoring of the respective dependent variables into account and use Tobit. We find no gender difference in IQ, but boys are significantly more patient, more risk-taking, and less altruistic than girls. In columns (2), (4), (6) and (8), we add the interaction term "Male x low SES". We use OLS for all four regressions to ease comparison of the the coefficient of the interaction term. The results show that the SES gaps in IQ and economic preferences do not differ significantly for boys and girls. Bootstrapped standard errors (1000 bootstrap replications) are displayed in parentheses. Significance at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: SES gaps by risk domain

| | Risk-averse | Risk-neutral | Risk-seeking |
|---|---|---|---|
| | (1) | (2) | (3) |
| Low SES | 0.011 | −0.079* | 0.068* |
| | (0.047) | (0.045) | (0.041) |
| Observations | 435 | 435 | 435 |

**Notes**: The table shows coefficients of linear probability estimations, in which a binary indicator of the respective risk preference category is regressed on a low SES dummy that equals 1 for low and 0 for high SES families. The dependent variable equals 1 if a child is classified as risk-averse (risk-neutral, risk-seeking) and 0 otherwise. Section 2.3.2 contains the exact definitions of the risk preference categories. Bootstrapped standard errors (1000 bootstrap replications) are displayed in parentheses. Significance at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: SES gaps in IQ, patience, risk-taking, and altruism

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | Panel A: IQ | | |
| Parental education (stand.) | 0.350*** | | 0.257*** | 0.252*** |
| | (0.046) | | (0.060) | (0.060) |
| Log HH income (stand.) | | 0.309*** | 0.162*** | 0.160*** |
| | | (0.044) | (0.056) | (0.056) |
| Parental education x Log HH income | | | | −0.082* |
| | | | | (0.043) |
| | | Panel B: Patience | | |
| Parental education (stand.) | 0.250*** | | 0.171** | 0.162** |
| | (0.064) | | (0.079) | (0.080) |
| Log HH income (stand.) | | 0.235*** | 0.137* | 0.131 |
| | | (0.068) | (0.083) | (0.083) |
| Parental education x Log HH income | | | | −0.132** |
| | | | | (0.055) |
| | | Panel C: Risk-taking | | |
| Parental education (stand.) | −0.110* | | −0.050 | −0.053 |
| | (0.065) | | (0.071) | (0.071) |
| Log HH income (stand.) | | −0.134** | −0.106 | −0.108 |
| | | (0.062) | (0.067) | (0.068) |
| Parental education x Log HH income | | | | −0.056 |
| | | | | (0.065) |
| | | Panel D: Altruism | | |
| Parental education (stand.) | 0.140*** | | 0.142** | 0.143** |
| | (0.046) | | (0.056) | (0.057) |
| Log HH income (stand.) | | 0.077* | −0.004 | −0.004 |
| | | (0.046) | (0.056) | (0.056) |
| Parental education x Log HH income | | | | 0.015 |
| | | | | (0.044) |

**Notes**: The table shows coefficients of regressions, in which IQ or economic preferences are regressed on a low SES dummy that equals 1 for low and 0 for high SES families. Panel A and D are estimated using OLS. In Panel B and C, we take the censoring of the respective dependent variables into account and use Tobit. Average parental education and log household income are standardized within the analyzed sample. Standard errors are bootstrapped standard errors (1000 bootstrap replications). For all regressions: $N = 435$. Significance at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Child IQ and preference changes in response to changes in parental resources or parental investments

| Policies | Actual | | Compulsory educ min 13 years | | Income support min 1,065 EUR | | Style +0.2 sd | | Time +0.2 sd | | Style and time +0.2 sd | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | SES Gap | SE | SES Gap | SE | SES Gap | SE | SES Gap | SE | SES Gap | SE | SES Gap | SE |
| **Developmental inputs** | | | | | | | | | | | | |
| Education | 4.071 | (0.242) | 2.600 | (0.172) | 4.072 | (.242) | 4.072 | (0.242) | 4.072 | (0.242) | 4.072 | (0.242) |
| Income | 838.760 | (53.805) | 746.205 | (54.761) | 678.905 | (51.371) | 838.761 | (53.804) | 838.761 | (53.805) | 838.761 | (53.805) |
| Style | 0.249 | (0.092) | 0.177 | (0.077) | 0.147 | (0.078) | 0.062 | (0.091) | 0.262 | (0.091) | 0.062 | (0.091) |
| Time | 0.761 | (0.088) | 0.514 | (0.067) | 0.673 | (0.071) | 0.761 | (0.088) | 0.561 | (0.088) | 0.561 | (0.088) |
| **Child IQ and preferences** | | | | | | | | | | | | |
| IQ | 0.647 | (0.105) | 0.472 | (0.054) | 0.509 | (0.055) | 0.557 | (0.059) | 0.557 | (0.059) | 0.498 | (0.059) |
| Patience | 0.348 | (0.148) | 0.328 | (0.047) | 0.374 | (0.047) | 0.202 | (0.052) | 0.190 | (0.052) | 0.131 | (0.052) |
| Risk-taking | 0.226 | (0.125) | 0.316 | (0.047) | 0.373 | (0.048) | 0.070 | (0.056) | 0.044 | (0.056) | −0.017 | (0.056) |
| Altruism | 0.212 | (0.101) | 0.219 | (0.052) | 0.254 | (0.050) | 0.125 | (0.057) | 0.129 | (0.057) | 0.062 | (0.057) |

**Notes**: The table displays SES gaps of developmental inputs and child outputs. The first column presents the actual gap. The other columns represent predicted gaps as they would prevail in response to five different policy changes: (1) A compulsory schooling policy which requires both parents to obtain 13 years of education (A-level equivalent). (2) A (tax-neutral) income support policy to poor families, which raises the incomes of poor families to the threshold level of 1,065 EUR. (3) A policy which raises parenting style investments by 20% of a standard deviation. (4) A policy which raises parental time investments by 20% of a standard deviation. (5) A policy which raises both parenting style investments and parental time investments by 20% of a standard deviation. Counterfactual outcomes for affected families are predicted using estimates of model equations (1) and (2). Counterfactual incomes in response to a compulsory education policy (1) were computed using estimates of equation (B5). The table shows coefficients of regressions where the respective developmental input or outcome is regressed on a low SES dummy. Standard errors are bootstrapped using 1,000 bootstrap replications.

## A.3 Additional figures


Figure A1: Toys arranged in four categories (example). To measure risk and social preferences, we introduced an experimental currency called "stars". After the interview, children could exchange the number of stars that they had collected for toys. The toys were arranged in four categories that visibly increased in value and attractiveness. The children knew that with more stars they could choose a toy from a higher category. To ensure that each star was valuable, we converted any remaining stars into Lego bricks, after the child had chosen his/her toy.

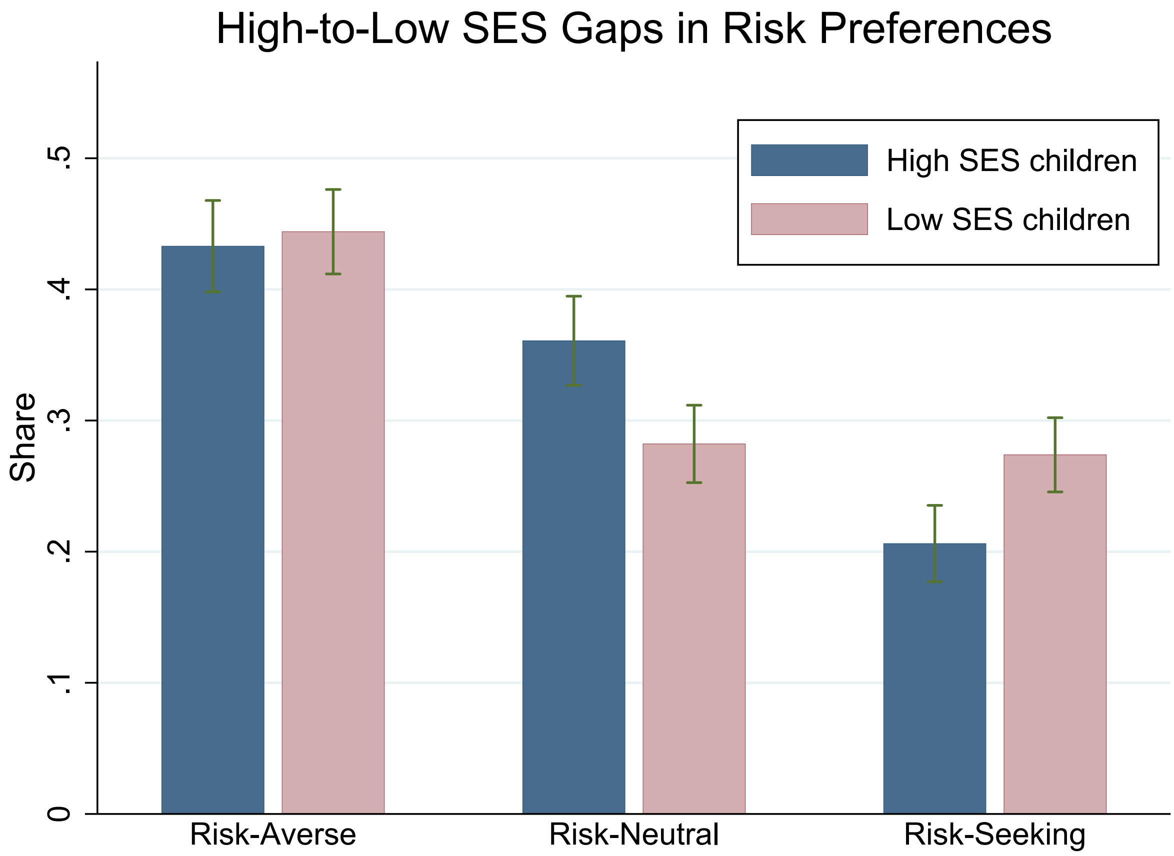



Figure A2: The figure displays the shares of children categorized as risk-averse, risk-neutral or risk-seeking by SES (for definitions of the risk categories, see Section 2.3.2). Error bars indicate bootstrapped standard errors (1000 bootstrap replications). Table A5 provides test results on whether the shares differ significantly by SES.

# B Additional data descriptions and analyses

## B.1 Robustness checks: weighting

### B.1.1 Weighting scheme 1: representative population

To allow for representative interpretable evidence, we compare our sample to the population of families in Germany. The comparison comprises parental SES, as well as maternal intellect, maternal patience, maternal willingness to take risks and maternal altruism. As a reference, we make use of data from the German Socio-Economic Panel (SOEP) (Wagner, Frick, and Schupp, 2007). The data are collected yearly and are representative of the German population. The SOEP consists of more than 20,000 individuals in more than 10,000 households. We compare the families in our sample to families with children under the age of 14 in the SOEP. In order to compare the samples along all dimensions which are of importance for our study, we elicited SES in the same way as in the SOEP and used the same validated survey questions about maternal intellect and economic preferences in both data sets.

For both samples we use the SES definition described in Section 2.2. Concerning patience, we use the measure validated by Vischer et al. (2013), and for risk preferences, we employ the measure validated by Dohmen et al. (2011). As a proxy for altruism, we use a measure of the Big Five dimension agreeableness. For details on this measure and its relation to social preferences, see Becker et al. (2012). As a proxy for intelligence, we use a measure of the Big Five dimension openness/intellect. For a discussion on the relation of IQ and openness/intellect and an example of this approach see Rustichini et al. (2016). For a detailed description of the Big Five inventory used for the mothers in our sample and in the SOEP, see Gerlitz and Schupp (2005).[40]

Table B1 shows how the measures described above compare between our sample and the SOEP sample. The share of high SES families in our sample is moderately higher than in the SOEP (44.6% vs. 37.8%). In order to compare the samples in terms of intellect and economic preferences, we standardized the measures using the SOEP as a reference, i.e., the mean in the SOEP is zero in all dimensions. For our sample, we find that mothers are more intelligent, more willing to take risks, and more altruistic than mothers of children in the SOEP. There is no significant difference in patience. These findings are in line with the observation that high SES families are slightly over-represented in our sample.

[40]The analysis in this section is based on SOEP (2010), the most recent available data at the time of sampling. The measures where collected in 2008, the only exception is patience which was collected in 2009.

Table B1: Comparison to a representative sample

| Variable | SOEP | Analyzed sample | Sign. difference |
|---|---|---|---|
| Share high SES | 37.8 % | 44.6 % | *** |
| Maternal intellect | 0.0 | 0.422 | *** |
| Maternal patience | 0.0 | 0.086 | |
| Maternal willingness to take risk | 0.0 | 0.576 | *** |
| Maternal altruism | 0.0 | 0.283 | *** |

**Notes**: Family characteristics of the analyzed sample ($N = 435$) and in the SOEP ($N = 1,812$). $t$-tests indicate significant differences at * p < 0.1, ** p < 0.05, *** p < 0.01.

In order to check to what extent these deviations from a representative sample affect our results, we re-weigh our data according to the SES, preference and skill distribution in the SOEP. To calculate these weights, we generate 32 groups based on the combination of the binary SES criterion and median splits of the four skill and preference dimensions. We re-weigh the observations in our sample to produce the same distribution over the 32 groups as in the SOEP using inverse probability weights. We also use these weights whenever we standardize a measure. The re-weighted main results are displayed in Figure B1. The resulting effect sizes are very similar to those from the unweighted regression, suggesting that selective participation does not bias our results.

### B.1.2 Weighting scheme 2: attrition

As described in Section 2.1 we conducted two rounds of data collection within one developmental period. The sample in data collection 1 consists of 519 children and their mothers. 442 of these families also took part in the second data collection. For 435 children (83.8%), we can construct a balanced data set with all required information (preference and skill measures of children and mothers, SES and investment measures). For these 435 families we have two measures of each dimension of interest (from the children), collected within one developmental period.

To check for selective attrition related to socio-economic background, economic preferences, or IQ of the child, we re-weigh the observed data using inverse probability weighting (IPW). The predictions come from a probit model of a binary selection indicator (indicating if an observation is either only available in data collection 1 ($N = 84$) or in the balanced data set ($N = 435$)) as a function of parental SES, child IQ, patience, risk-taking and altruism measured in data collection 1. We repeated the main analysis shown in Figure 1 using these weights. The results of the regressions using IPW are shown in Figure B1. The effects sizes are very similar to the unweighted effect sizes, suggesting that selective attrition does not bias our results.

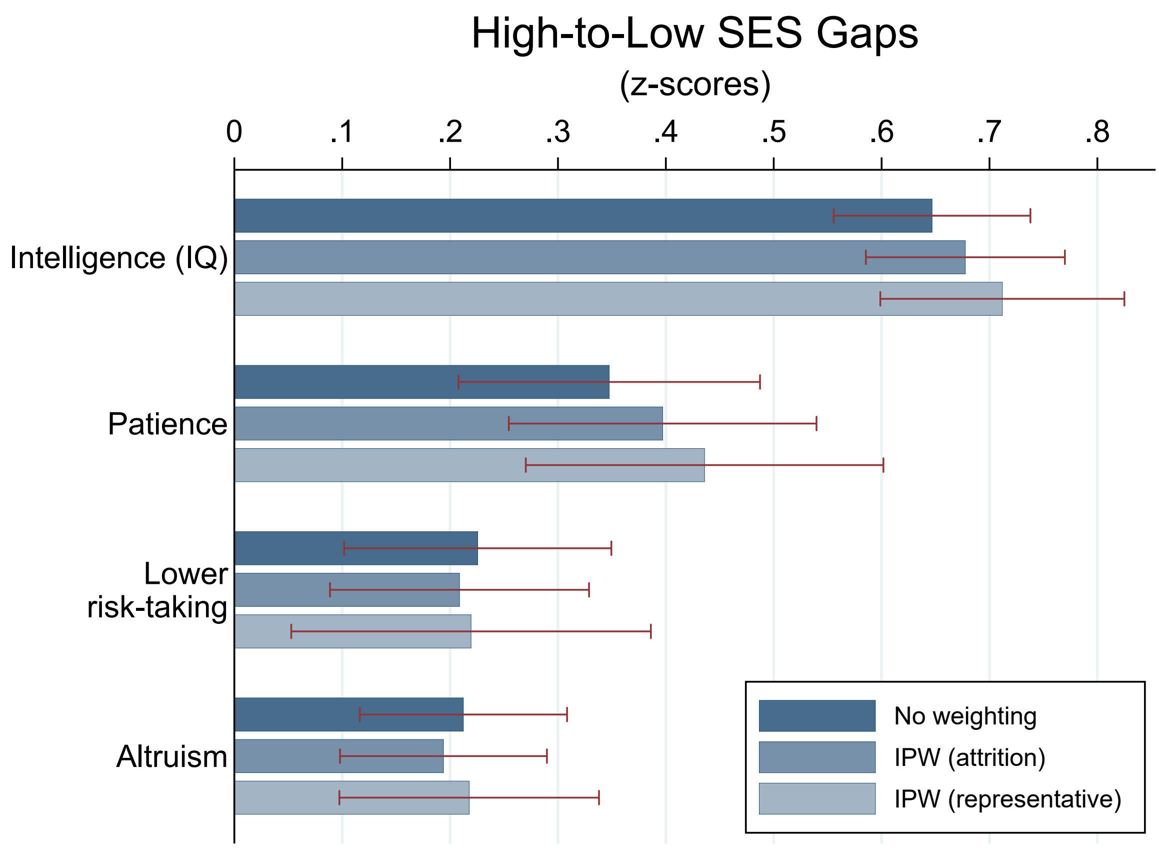



Figure B1: The figure displays gaps in IQ and economic preferences between elementary school children from high and low SES families. The horizontal bars represent coefficients of a dummy variable that equals 1 for high and 0 for low SES households in regressions of IQ or preferences on this SES dummy (OLS for IQ and altruism, Tobit for patience and risk-taking). The first, dark blue set of bars show the results of the unweighted main analysis as in Figure 1. The second light blue and third grey set of bars show weighted least-square (IPW) estimates, respectively addressing possible selective attrition or the lack of representativeness of our sample. Error bars indicate bootstrapped standard errors, for the IPW estimates obtained using the BWR-scheme (bootstrap with replacement) by Kolenikov (2010).

## B.2 Maternal skills and preferences

Our measure of maternal IQ is based on the Standard Progressive Matrices Plus test (SPM Plus, 10 item short version). The measure of IQ corresponds to the standardized number of correct answers. IQ has been shown to be very stable for adults (see, Borghans et al., 2008, for a discussion). Therefore, and due to time constraints, maternal IQ was only elicited in data collection 2.

Concerning maternal preferences we use questionnaire measures validated by Falk et al. (2016). For maternal time preference we use the measure: “When it comes to financial decisions, how do you assess your willingness to abstain from things today so that you will be able to afford more tomorrow. Please indicate on the scale, where the value 0 means 'not at all willing to abstain today' and the value 10 means 'very willing to abstain today'".

For maternal risk preferences we use the measure "How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please indicate on the scale, where the value 0 means: 'not at all willing to take risks' and the value 10 means: 'very willing to take risks'". For a detailed discussed on this item see also Dohmen et al. (2011).

To measure maternal altruism, mothers played two binary hypothetical dictator games in which they could distribute money (in euro) between themselves and another mother: in decision A they could choose between the distributions (16, 4) and (10, 10) and in decision B they could choose between the distributions (6, 18) and (10, 10).[41] The first value indicates their own monetary amount; the second value indicates the amount for the receiving mother. Our measure of maternal altruism is the sum of altruistic choices ((10, 10) in decision A and (6, 18) in decision B).[42]

## B.3 Test-retest stability of experimental measures of preferences

In our sample of elementary school children, the Spearman Rank correlations between our measures taken in data collection 1 and our measures taken in data collection 2 (16 months in between) are 0.301 for time preferences, 0.292 for risk preferences, and 0.382 for altruism ($p < 0.01$ for all preferences). To put these test-retest properties into perspective, we compare them to those obtained from data on young adults (for details on the data, see Falk et al., 2016). For this group of young adults, age-adapted experimental measures on the same preference domains were collected twice with only one week in between. Although based on adults, and despite the small time interval between measurements, these data display test-retest correlations which, except for patience, are only slightly higher than the ones we find in our data, see table B2.

It seems unlikely that preferences of adults have changed within a one-week interval. The observed variation in both samples therefore suggests that most of the instability across data collections is due to measurement error rather than variation in the underlying preferences. Additional evidence in support of the stability of preferences of children comes from, e.g., Mischel, Shoda, and Rodriguez (1989), Moffitt et al. (2011), Golsteyn, Grönqvist, and

[41] Falk et al. (2016) show that, in the context of social preferences, hypothetical decisions are good proxies for incentivized decisions.

[42] Due to time constraints, maternal altruism was only elicited in the first data collection.

Table B2: Stability of preferences: test-retest Spearman correlations

| **Sample** | **Patience** | **Risk-taking** | **Altruism** |
|---|---|---|---|
| Elementary school children | $\rho = 0.301$ (16-month interval) | $\rho = 0.292$ (16-month interval) | $\rho = 0.382$ (16-month interval) |
| Young adults | $\rho = 0.672$ (1-week interval) | $\rho = 0.347$ (1-week interval) | $\rho = 0.445$ (1-week interval) |

**Notes**: For details on the sample of young adults, see Falk et al. (2016).

Lindahl (2014) and Cadena and Keys (2015), who show that measures elicited during childhood have predictive power for teenage and adult outcomes. Related evidence using our own data is presented in Section B.5 and table A3.

## B.4 Empirical relations among IQ and preferences

Table B3 displays the Spearman correlations among our four measures of interest. The overall correlation pattern is mostly in line with that found for adults: positive correlations between IQ and patience are found, e.g., in Dohmen et al. (2010) and Humphries and Kosse (2017). Burks et al. (2009) also indicate a positive correlation between patience and risk-taking. For large scale evidence on the relations at the country level, see Falk et al. (2018). Angerer et al. (2015a) present related results concerning altruism.

Table B3: Spearman correlations among IQ and economic preferences

| | IQ | Patience | Risk taking | Altruism |
|---|---|---|---|---|
| IQ | 1 | | | |
| Patience | 0.290*** | 1 | | |
| Risk-taking | -0.063 | 0.100** | 1 | |
| Altruism | 0.119** | -0.099** | -0.223*** | 1 |

**Notes**: $N = 435$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

## B.5 Follow-up surveys: teenage outcomes

In the years 2015 and 2016 which is four and five years after the first data collection, we collected follow-up data on teenage outcomes of the children in our sample. In 2016 the participants are on average 13 years old and we were able to collect information on about 80% (348 of 435) of the sample that is used in the main analysis in Section 3 (see Table A3).

In 2016 we asked mothers and children to state the most recent grades of the child in the subjects of mathematics, German language and first foreign language. To calculate the grade point average (GPA), we take the average of mothers' and children's reports and average over these three (main) subjects. For convenience, we recode the data such that higher grades indicate better performance.

As a proxy for juvenile offending we asked the teenagers in 2016 to state on a 4-point scale how often they intentionally damaged or destroyed something which they did not own.

To measure social participation we asked the participants in 2015 to state on a 5-point scale how often they participate in youth group activities (as, e.g., boy scouts or environmental groups), sports activities or playing music. We aggregate the three ratings to yield one joint score.

## B.6 Robustness checks: experimental protocol

In table B4 we repeat the analysis shown in table A2, adding control variables which might have influenced the experimental measures. A possible concern is a potential bias driven by the amount of stars earned within the testing situation (in-experiment wealth). We therefore include controls for the number of stars which the children had already earned during the sequence of experiments before each respective experiment took place. Another possible concern are potential doubts of the children in the experimental protocol (e.g., in the reliability of the mail service, in the likelihood that another family member will keep the letter for him or herself, ...). In this case the incentivized measures could potentially also reflect trust and risk-taking. We therefore include controls for risk-taking and trust.

Note that in order to prevent in-experiment wealth effects we put aside the money earned in each experiment in an extra, closed paper bag. To eliminate uncertainty of future payments we explicitly addressed the letter (delivering the delayed money) to the children themselves, wrote the address on the envelope and put the saved amount of money in the envelope while the children were watching. We also handed out contact details for questions or requests.

To explore if heterogeneities in in-experiment wealth or trust and risk-taking bias the SES gaps displayed above, we repeat the analysis shown in table A2, adding measures of in-experiment wealth, risk-taking and trust[43] as control variables[44]. Comparing results in tables A2 and B4 shows that the estimated SES gaps are not biased by these potential confounding factors.

[43]The trust measure of children stems from a 3-item questionnaire and includes the following items: "One can trust other people", "Other people have good intentions towards me" and "One can rely on other people, even if one does not know them well", for details see Kosse et al. (2019).

[44]Although this procedure is common practice in experimental economics, conditioning on other outcome variables comes at the cost of potentially introducing a bad control problem (Angrist and Pischke, 2009). Therefore these conditional correlations should be treated with caution.

Table B4: Robustness check: SES gaps in patience, risk-taking and altruism with additional control variables

| | Patience | Risk-taking | Altruism |
|---|---|---|---|
| | (1) | (2) | (3) |
| Low SES | −0.383*** | 0.209* | −0.181* |
| | (0.139 ) | (0.122 ) | (0.094 ) |
| **Control variables**: | | | |
| In-experiment wealth | X | X | X |
| Trust | X | X | X |
| Risk-taking | X | | X |
| Observations | 435 | 435 | 435 |

**Notes**: In columns (1) and (2), we use a Tobit model. Column (3) is estimated using OLS. Bootstrapped standard errors (1000 bootstrap replications) are displayed in parentheses. Significance at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

## B.7 Robustness checks: wealth effects

A further possible concern is potential heterogeneity in the valuation of incentives between children from high and low SES families due to different amounts of available monetary resources. To check if the availability of different monetary resources affects the relation between SES and the incentivized preference measures, we repeat the analysis shown in table A2 and add the weekly amount of pocket money as a proxy for available monetary resources as control variable. For a discussion of this approach also see Sutter et al. (2013). The results are shown in table B5, the estimates of the SES gaps are in line with the raw gaps shown in table A2. This comparison suggests that the estimated SES gaps are not biased by heterogeneities in available monetary resources. None of the estimated coefficients of pocket money is statistically different from zero.

Table B5: Robustness check: SES gaps in patience, risk-taking and altruism with additional control variables

| | Patience | Risk-taking | Altruism |
|---|---|---|---|
| | (1) | (2) | (3) |
| Low SES | −0.370*** | 0.223* | −0.220** |
| | (0.136) | (0.124) | (0.097) |
| Amount pocket money (in Euro per week) | 0.047 | 0.037 | 0.003 |
| | (0.033) | (0.032) | (0.034) |
| Observations | 433 | 433 | 433 |

**Notes**: In columns (1) and (2), we use a Tobit model. Column (3) is estimated using OLS. Bootstrapped standard errors (1000 bootstrap replications) are displayed in parentheses. Two observations are missing due to missing information on pocket money. Significance at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

## B.8 Robustness checks: parental education

Throughout the paper our measure of parental education is the average years of education of both mother and father.[45] This could be misleading if the educational attainment of mother and father is very heterogeneous within a family and/or if the relation between education and children's IQ and preferences is different for mother and father. In this respect it is important to point out that – in line with evidence of assortative mating (Eika, Mogstad, and Zafar, 2019) – years of education of mother and father are highly correlated (Spearman's $\rho = 0.616, p < 0.01$).

In table B6 we display results on the association between parental education and children's IQ and preferences separately for mothers and fathers. Given the strong correlation in educational attainment it is not surprising that the correlations with IQ and preferences of children are very similar.

[45] Information on education of the father is provided by the mother and refers to the "current partner of the mother". In 88% of the cases this is the biological father of the child.

Table B6: Robustness: parental years of education

| | IQ | Patience | Risk-taking | Altruism |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Average years of education | 0.119*** | 0.085*** | −0.037* | 0.047*** |
| | (0.016) | (0.022) | (0.022) | (0.016) |
| Maternal years of education | 0.108*** | 0.075*** | −0.038* | 0.040*** |
| | (0.014) | (0.020) | (0.020) | (0.014) |
| Paternal years of education | 0.084*** | 0.062*** | −0.047** | 0.037** |
| | (0.015) | (0.022) | (0.023) | (0.018) |

**Notes**: The table shows coefficients of regressions in which the respective skill or preference is regressed on a constant and either average or maternal or paternal years of education 1. Columns 1 and 4 are estimated using OLS. In columns 2 and 3 we take the censoring of the respective dependent variable into account and estimate a Tobit model. Bootstrapped standard errors (1000 bootstrap replications) are displayed in parentheses. The number of observations is 435 except for the regressions using paternal education which, due to missing information, only rely on 351 observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

## B.9 Robustness checks: single parenthood

Single parent families often differ in terms of financial and non-financial resources (McLanahan, 2009), such that single parenthood is potentially important in our context. Yet, single parenthood explains surprisingly little of the IQ and preference gaps (compare table B7 below to table A2).[46] The same holds true when we include single parent status as a covariate in the structural model presented in Section 4 (see top panel of table B8). Moreover, even when we restrict the sample to two-parent households only, we find that our results remain largely unaltered, except for a slight increase in the importance of parenting styles (see bottom panel of table B8).

These findings are in line with recent studies showing that family status matters relatively little in Germany compared the US (Francesconi, Jenkins, and Siedler, 2010). In fact, single parenthood in Germany is associated with achievement gaps that are about three times smaller than in the US (Woessmann, 2015). There are several institutional and cultural differences that may explain these findings. For example, the social safety net and a well-functioning public school system may reduce the economic pressure for single mothers to work full time. Moreover, irrespective of social class or family status, females shoulder most of the child rearing responsibilities in Germany (Aisenbrey and Fasang, 2017). Last, biological fathers tend to remain close to their children after a marital breakup. In our sample, separated fathers spend on average 8 hours per week as main caregiver of their

[46]Single parent status is defined as "not living together with a partner" at the time of sampling.

child which is not significantly less than fathers in two-parent families (see column (1) of table B9, information provided by the mother). Columns (2) and (3) of table B9 reveal that this pattern also does not significantly differ by SES. Consequently, the amount of time in which the father is "in charge" of the child explains little of the IQ and preference gaps (see columns (2), (4), (6) and (6) in table B7).

Table B7: SES gaps, single parent status and time of father with child

| | **IQ** | | **Patience** | | **Risk-taking** | | **Altruism** | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Low SES | −0.631*** | −0.622*** | −0.347** | −0.342** | 0.244** | 0.243* | −0.212** | −0.203** |
| | (0.091 ) | (0.091 ) | (0.139 ) | (0.140 ) | (0.124 ) | (0.125 ) | (0.098 ) | (0.099 ) |
| Single parent | 0.136 | 0.145 | 0.005 | 0.010 | 0.154 | 0.153 | 0.003 | 0.011 |
| | (0.096 ) | (0.096 ) | (0.151 ) | (0.152 ) | (0.129 ) | (0.130 ) | (0.105 ) | (0.105 ) |
| Time of father with child | | 0.061 | | 0.041 | | −0.007 | | 0.062 |
| (standardized) | | (0.051 ) | | (0.062 ) | | (0.070 ) | | (0.047 ) |
| Observations | 435 | 435 | 435 | 435 | 435 | 435 | 435 | 435 |

**Notes**: The table shows coefficients of regressions, in which IQ or economic preferences are regressed on a low SES dummy that equals 1 for low and 0 for high SES families. Columns (1), (2), (7) and (8) are estimated using OLS. In columns (3) to (6), we take the censoring of the respective dependent variables into account and use Tobit. For details on time of father with child see table B9. Standard errors are displayed in parentheses. Standard errors are bootstrapped standard errors (1000 bootstrap replications). Significance at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B8: Production function (average marginal effects) of the structural models controlling for single parenthood (top panel) and restricting the sample to two-parent families (bottom panel)

| | | | | |
|---|---|---|---|---|
| **All households** | | | | |
| $AME_{M^{l}}$ | 0.579*** | 0.445*** | 0.262*** | 0.557*** |
| | (0.087) | (0.100) | (0.061) | (0.109) |
| $AME_{\text{Style}}$ | 0.311*** | 0.341*** | 0.414*** | 0.424*** |
| | (0.074) | (0.091) | (0.069) | (0.067) |
| $AME_{\text{Time}}$ | 0.367*** | 0.464*** | 0.623*** | 0.436*** |
| | (0.071) | (0.121) | (0.097) | (0.086) |
| Observations | 435 | 435 | 435 | 435 |
| **Two-parent households** | | | | |
| $AME_{M^{l}}$ | 0.655*** | 0.318*** | 0.257*** | 0.624* |
| | (0.107) | (0.098) | (0.086) | (0.365) |
| $AME_{\text{Style}}$ | 0.331*** | 0.423*** | 0.495*** | 0.448*** |
| | (0.092) | (0.123) | (0.099) | (0.166) |
| $AME_{\text{Time}}$ | 0.314*** | 0.566*** | 0.596*** | 0.497** |
| | (0.091) | (0.173) | (0.110) | (0.210) |
| Observations | 291 | 291 | 291 | 291 |

**Notes**: The reported SEs (in parentheses) were bootstrapped using 1,000 bootstrap replications. Significance stars at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B9: Time of father with child

| | Time father "in charge" of child (hours per week) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Single parent | −2.116 | | −3.560 |
| | (1.736) | | (2.486) |
| Low SES | | −2.167 | −3.199 |
| | | (1.733) | (2.203) |
| Single parent x low SES | | | 2.190 |
| | | | (3.650) |
| Observations | 435 | 435 | 435 |

**Notes**: The dependent variable is the time per week (in hours) in which the father is "in charge" of the child (indicated by the mother). As in section B.11.1 we use the average over both data collections. Coefficients are OLS estimates. Bootstrapped standard errors (1000 bootstrap replications) are displayed in parentheses. Significance at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

## B.10 Linking maternal traits to SES

Maternal IQ and preferences translate into higher levels of education. To illustrate this relationship, we link education and income (as measures of socio-economic status) to maternal traits by specifying a simple reduced-form system of equations as:

$$\begin{aligned} E_i &= \beta_0^E + \beta_C^E M_i^C + \beta_T^E M_i^T + \beta_R^E M_i^R + \beta_A^E M_i^A + \beta_Z^E Z_i + u_i^E \\ y_i &= \beta_0^y + \beta_C^y M_i^C + \beta_T^y M_i^T + \beta_R^y M_i^R + \beta_A^y M_i^A + \beta_E^y E_i + \beta_Z^y Z_i + u_i^y \end{aligned} \tag{B5}$$

where $E$ denotes parental education, $y_i$ is log equivalence household income, and $Z_i$ is a vector of control variables comprising a measure of single parenthood, the number of siblings, and the child's age. Moreover, for a given mother, the errors may correlate across equations, with $\mathrm{E}[u_i^E u_i^y | M, E, Z] = \sigma^S$. The above system of equations (B5) serves two purposes. First, estimates from the above system of equations help us to better understand the extent to which socio-economic status explains intergenerational correlations in IQ and preferences. Second, they provide an additional form of anchoring, that is, a link between traits and economic outcome variables. Such anchoring can be informative above and beyond the natural anchoring of our variables in incentivized experimental behaviors.

Table B10: Parental SES

| | High SES (1) | | Parental education (2) | | Log HH income (3) | |
|---|---|---|---|---|---|---|
| IQ | 0.145*** | (0.023) | 0.969*** | (0.151) | 0.075*** | (0.021) |
| Altruism | −0.020 | (0.024) | −0.189 | (0.149) | 0.028 | (0.020) |
| Patience | 0.051** | (0.025) | 0.526*** | (0.144) | 0.000 | (0.019) |
| Risk | 0.026 | (0.023) | 0.267** | (0.134) | 0.032* | (0.019) |
| Parental education | | | | | 0.075*** | (0.008) |
| Observations | 435 | | 435 | | 435 | |

**Notes**: Standard errors (in parentheses) are bootstrapped using 1000 bootstrap replications. The equation for log HH income comprises a dummy for single parenthood, parental age and parental age squared. Significance at * p < 0.1, ** p < 0.05, *** p < 0.01.

Table B10 presents results on the relationship between socio-economic status and maternal traits. The results in column 2 suggest that maternal IQ and maternal patience are strongly related to the average education level in the household. In particular, we find that maternal intelligence is the strongest predictor of education, to the extent that a one standard deviation increase in maternal IQ maps into 0.97 additional years of education. The coefficients of maternal patience and her willingness to take risks are roughly half and one third of the size of the intelligence effect, but also significant. This result is in line with predictions of standard human capital models, which predict a negative relationship between the (subjective) discount rate and the number of years of education (Ben-Porath, 1967). The acquired level of education can be used to generate household income either through market work or via improved marriage market opportunities. Column 3 of table B10 shows that the return to an additional year of education amounts to around 7.5 percent of household income in our data. In addition, we find that IQ and willingness to take risk are positively related to household income. A one standard deviation increase in IQ raises household income by 7.5 percent and a one standard deviation increase in the willingness to take risks raises it by 3.2 percent.

## B.11 Further measures of parents

### B.11.1 Parental investment measures

The information on parenting style and time investments are collected via the questionnaire answered by mothers.[47] To estimate latent parenting styles, we use three indicators of parenting style investments (for an overview and a detailed description of the parenting style measures, see Thönnissen et al., 2015, and the references therein).[48] First, *parental warmth* (two items: (i) "I show my child with words and gestures that I like him/her." (ii) "I praise my child.") measures the extent to which parents praise their child and their tendency to show love and affection. Second, *psychological and behavioral control* (four items: (i) "If my child does something against my will, I punish him/her." (ii) "I make it clear to my child that he/she is not to break the rules or question my decisions." (iii) "I think my child is ungrateful when he/she does not obey me." (iv) "I do not talk to my child for a while when he/she did something wrong.") indicates child punishments. Third, parental *monitoring* (two items: (i) "When my child goes out, I know exactly where he/she is." (ii) "When my child goes out, I ask what he/she did and experienced.") indicates the degree to which parents are informed about the whereabouts and doings of their child. These eight items are used to extract one latent parenting style factor as explained in Section 4.3.1.

Parental quality time investments are constructed from a short time diary in which parents report the frequency of a large number of activities with the child during the past two weeks. Highly interactive joint activities comprise, e.g., joint meals, playing board games and

[47]The data on time investments were collected in both data collections; we therefore use averages to reduce measurement error. Parenting styles are assumed to be stable within one developmental period. Therefore, and because of time constraints for data collection, information on parenting style was only elicited in data collection 2.

[48]In sum, we use eight items which are rated on a 5-point Likert scale, respectively.

playing an instrument together. Joint activities which require a low degree of interaction comprise, e.g., grocery shopping, watching TV and playing video games. In the analysis, our measure of parental time investment is the share of highly interactive activities (see Section 4.3.1). This approach allows us to hold the maternal time budget for non-work related activities fix, which in itself might be a function of familial contexts that are outside of our framework, such as the number of children or the number of available caregivers.

Table B11 provides summary statistics of each of the above measures for high and low socio-economic status families, as well as the estimated loadings in the measurement system of the parenting style factor. It shows that, with the exception of parental warmth, high socio-economic status parents score significantly higher on all investment indicators.

Table B11: Parental investment measures

| **Variables** | $\mu_h$ | $\mu_l$ | **diff** | **p-value** | **loading** |
|---|---|---|---|---|---|
| Parental warmth | 0.070 | 0.214 | −0.144 | 0.12 | 0.347 |
| Parental control | −0.300 | −0.062 | −0.238 | 0.01 | −0.050 |
| Parental monitoring | 0.230 | 0.047 | 0.184 | 0.03 | 1 |
| Share of highly interactive activities | 0.549 | 0.519 | 0.03 | 0.00 | - |

**Notes**: $\mu_h$ and $\mu_l$ indicate mean values for the high and low SES groups respectively. Reported p-values correspond to a t-test for the equality of means.

### B.11.2 Satisfaction with child development

Our aim is to approximate the process of a child's IQ and preference development until mid-childhood. However, we only observe parenting style and time investments at one particular developmental stage. Thus, our model estimates might be biased if the parental investments, parenting style and quality time respond to recent unobserved developmental shocks. We therefore developed a survey question, which specifically asks parents about their satisfaction with the child's developmental process.

To measure how satisfied mothers are with the development of their child, we asked the question: "All together, how satisfied are you with your child's development in the last year?" Answers were given on an 11-point scale with 0 meaning "completely dissatisfied" and 10 meaning "completely satisfied". As all measures directly related to children this measure was elicited in both data collections, which allows us to use the mean over both points in time.

## B.12 Assortative mating regarding preferences and investments

Our data only contain only limited information about secondary caregivers, as only the main caregiver (mostly the mother) responded to the survey questions and took part in the IQ test (see Section B.11). The information on education of the fathers used in section B.8 stems from reports by the mother. Hence, our analyses rely on the assumption that maternal IQ, preference and investment measures are a reasonable proxy also for paternal inputs, e.g., because of assortative mating. Such assortative mating on preferences and abilities is reasonable from a theoretical perspective (Bisin and Verdier, 2000, 2001). Moreover, the empirical literature finds within-couple correlations between 0.3 to 0.5 for IQ, patience, risk taking and altruism, respectively (Mascie-Taylor and Vandenberg, 1988; Kimball, Sahm, and Shapiro, 2009; Dohmen et al., 2012; Arrondel and Frémeaux, 2016).

Regarding the similarity of parental investments by fathers and mothers, we have conducted additional analyses using data of the SOEP (2017). These data contain the same style investment measures that are used in our main analysis (see Section B.11.1) for *both* parents of 8-years old children in the years 2010 to 2016 (number of families = 1,478).[49] The results are shown in table B12. The correlation between maternal and paternal parenting styles is statistically significant and the magnitude of the correlation is in a similar range as the within-couple correlations for preferences and IQ reported in the literature. Moreover, the results in column (2) indicate that the between correlation does not differ for low and high SES families.

Thus, since mothers and fathers seem to be relatively similar regarding their economic preferences, IQ, and parental investments, we argue that our main caregiver information is a reasonable proxy for parental investments within family.

[49]For the analysis in this section we use a score of the parental style items.

Table B12: Correlations of style investments between mother and father

| | Style Investment mother (standardized) | |
|---|---|---|
| | (1) | (2) |
| Style investment father (standardized) | 0.357*** | 0.307*** |
| | (0.027 ) | (0.038 ) |
| Low SES | | −0.118** |
| | | (0.048 ) |
| Style investment father x low SES | | 0.068 |
| | | (0.053 ) |
| Observations | 1,478 | 1,478 |

**Notes**: Style measures of father and mother were standardized such that the coefficient in columns (1) can be interpreted as Pearson correlation coefficients. The low SES dummy follows the definition in section 2.2. Coefficients are OLS estimates. Bootstrapped standard errors (1000 bootstrap replications) are displayed in parentheses. Data source: SOEP (2017). Significance at * p < 0.1, ** p < 0.05, *** p < 0.01.

## B.13 Parenting style factor and alternative estimates

We employ a latent factor model to extract latent parenting style. For our preferred model specification, we use a model with a flexible distributional factor structure in form of a mixture distribution. Our setup is thus similar to the one presented in Carneiro, Hansen, and Heckman (2003), Heckman, Stixrud, and Urzua (2006) or Heckman, Pinto, and Savelyev (2013). We assume that the observed measurements ($\mathcal{M}^S$) of parenting practices are additively separable in the natural logarithm of the latent parenting factor, a function of maternal IQ and preferences ($M^P$) and household characteristics ($X$). Then, for family $i$ and measurement $k$, we can write:

$$\mathcal{M}^S_{k,i} = \mu_k + M^P_{k,i}\gamma_k + X_{k,i}\beta_k + \lambda_k \ln(I^S) + \epsilon_{k,i} \qquad \text{for } k = 1, ..., K, \tag{B6}$$

where the terms $\mu_k$ are intercepts, $\lambda_k$ are factor loadings and $\epsilon_{k,i}$ are measurement errors. Measurements are standardized to have a mean of zero and standard deviation of one (using representative weights, see Section B.1). Since the scale of each factor is arbitrary, we set the factor loading in the first measurement equation to unity ($\lambda_1 = 1$). Furthermore, we assume $E[\epsilon_{k,i}] = 0$ for all $k = 1, ..., K$ and that the measurement errors are independent across equations and the latent factor. Finally, we require $K > 2$ to ensure identification. The distribution of $I^S$ is flexibly approximated by a mixture of two normal distributions, such that the probability density function can be written as:

$$f_I(\ln(I)) \sim \omega p_1(\ln(I^S_1)) + (1 - \omega)p_2(\ln(I^S_2)),$$

where $\omega$ is the mixture weight and $I_1^S \sim N(\mu_1, V_1)$ and $I_2^S \sim N(\mu_2, V_2)$. We estimate the above model (B6) using maximum likelihood by following the two-step procedure and code laid out in Sarzosa and Urzúa (2016), to recover the factor distribution. In the measurement part of the model, we proceed as in Heckman, Stixrud, and Urzua (2006), Heckman, Pinto, and Savelyev (2013), or Piatek and Pinger (2016) and include covariates that might jointly affect the measurement of parenting styles or that enter the production equation of child traits separately (such as maternal characteristics). Our aim is to recover the latent parenting style, to increase power by reducing measurement error and to reduce residual variance that might lead to biased estimates of equation (3).

As shown in detail in, e.g., Carneiro, Hansen, and Heckman (2003), in Sarzosa and Urzúa (2015) and in the appendix to Piatek and Pinger (2016), the above system is identified. In the following, we briefly repeat the main identification argument. First, the factor loadings, the variance of the factor and the measurement residual variances can be obtained from the covariance structure of the measurements. All covariances depend on the corresponding factor loading and on the variance of the factor, e.g., $\text{Cov}(M_1; M_2|X) = \lambda_{M_1}\lambda_{M_2}\sigma^2$. The ratios of the observed covariances then identify the ratios of the corresponding factor loadings up to a proportionality constant $\frac{\text{Cov}(M_1;M_2|X)}{\text{Cov}(M_2;M_3|X)} = \frac{\lambda_{M_1}}{\lambda_{M_3}}$. To achieve identification, we set the scale of the factor by fixing the first factor loading to one (in the equation for monitoring). Doing so, we can use the above relationship and other covariances to obtain the values of the factor loadings, the variance of the factor and the measurement residual variances. Second, given the factor loadings and measurement residual variances, the factor distribution is obtained from the joint distribution of measurements using Kotlarski's Theorem (see, pages 381 and 382 in Carneiro, Hansen, and Heckman (2003).)

Arguably, there are many alternative ways to aggregate parenting styles and the method of aggregation will lead to different results whenever parental behaviors translate into IQ and preferences differentially.[50] Moreover, the presence or absence of covariates in the measurement system may influence our estimates. In figure B2 and table B13 below, we thus present an alternative set of results, which is based on simple factor analysis (without covariates) and Bartlett (1937) scores. We find a somewhat smaller SES gap in parenting styles. Moreover, the impact of parenting styles on child IQ and preferences then slightly reduces for IQ, patience, and risk taking. It remains similar for altruism.

[50] As an example, parental punishment seems to (negatively) affect child altruism more strongly than child patience.

Figure B2: Parental Investments by Socio-economic Status

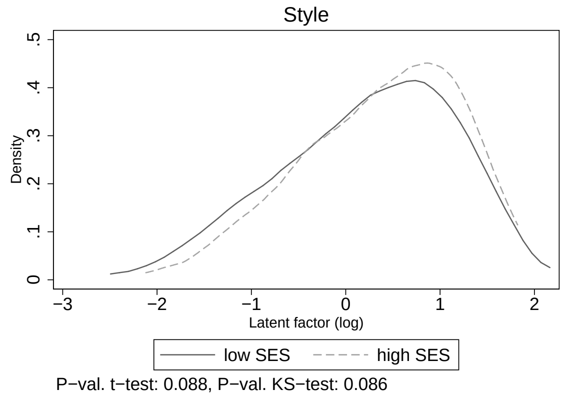



Table B13: Production function using principal component factor analysis and Bartlett factor scores (average marginal effects)

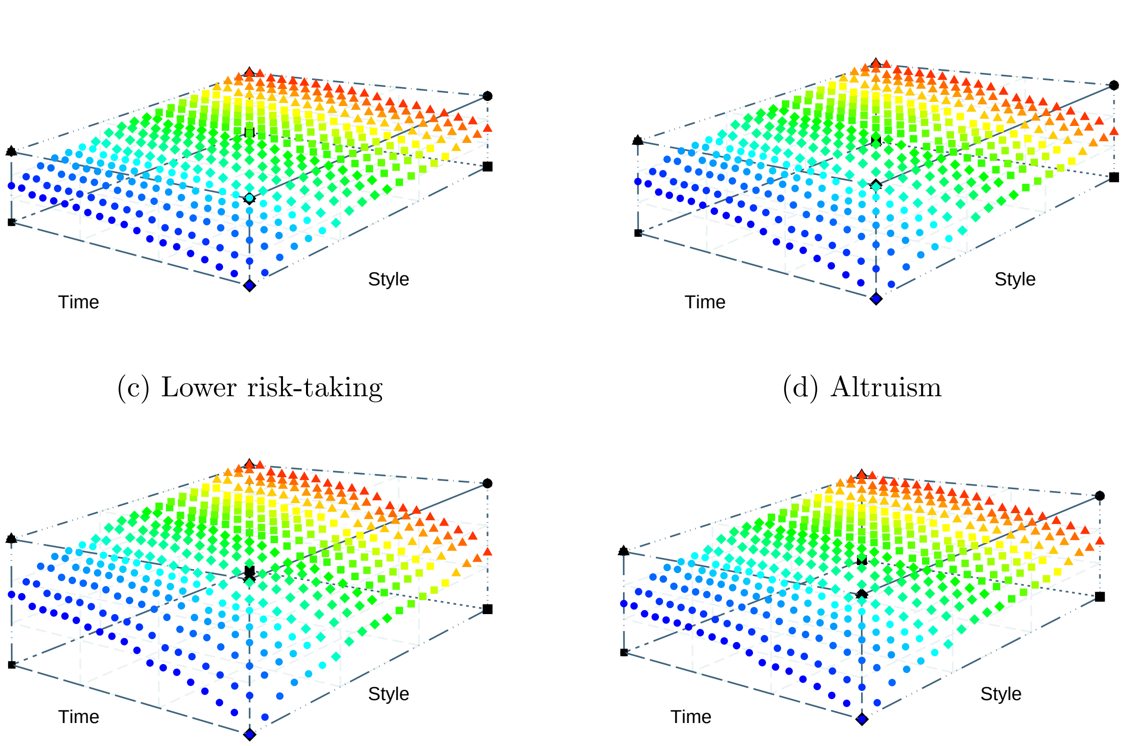
| **Marginal effects** | **IQ** | **Patience** | **Lower risk-taking** | **Altruism** |
|---|---|---|---|---|
| $\text{AME}_{M^l}$ | 0.499*** | 0.366*** | 0.233*** | 0.494*** |
| | (0.090) | (0.063) | (0.064) | (0.112) |
| $\text{AME}_{\text{Style}}$ | 0.307*** | 0.274*** | 0.432*** | 0.442*** |
| | (0.064) | (0.054) | (0.079) | (0.070) |
| $\text{AME}_{\text{Time}}$ | 0.289*** | 0.384*** | 0.623*** | 0.416*** |
| | (0.068) | (0.067) | (0.102) | (0.092) |
| Observations | 435 | 435 | 435 | 435 |

**Notes**: The reported SEs (in parentheses) were bootstrapped using 1,000 bootstrap replications. To achieve convergence of the model of child patience, we fix $\phi$ to the mean value of previous estimates. Significance stars at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

## B.14 Child IQ and preferences by ventile of parental investments

Figure B3 displays child outcomes for each ventile of the respective parental investment distribution. It shows that parenting styles are particularly important for the production of altruism, while time investments matter mostly for risk-taking. The graph also shows that changes in parenting styles and time investments are least effective in producing differences in child IQ and altruism, as long as the corresponding maternal characteristics are kept unchanged. The importance of an altruistic caregiver for the formation of altruism confirms the findings reported in Kosse et al. (2019).

Figure B3: Parental investments and child IQ and preferences




(a) IQ (b) Patience (c) Lower risk-taking (d) Altruism

**Notes**: The figure displays how child IQ and preferences (displayed in standard deviations on the y-axis) respond to parental investments. We use the standard convention that higher ventiles are associated with higher values of the variable.

## B.15 Robustness check: other maternal characteristics

The structural framework in the main part of the paper imposes that only the directly related maternal characteristic affects child preferences and IQ. Thus, for example, maternal IQ is only allowed to affect child's IQ but not risk taking or a child's patience. As a robustness check, we thus investigate whether other maternal characteristics also affect child IQ and preferences indirectly. As a simple test, and to keep the model estimable, we specify all other maternal characteristics to enter linearly. Thus, for example, for child IQ we estimate $\ln(P_i^{IQ}) = \ln(\Pi^{IQ}_{\text{SES}}) + \frac{1}{\phi^{IQ}} \ln[\gamma_M^{IQ} M_i^{IQ^{\phi^{IQ}}} + {\gamma_s}^{IQ} I_i^{S^{\phi^{IQ}}} + {\gamma_t}^{IQ} I_i^{T^{\phi^{IQ}}}] + \delta_M^P M_i^P + \delta_M^R M_i^R + \delta_M^A M_i^A + \eta_i^{IQ}$. The corresponding average marginal effects, displayed in Table B14, indicate that other maternal characteristics are of little importance after accounting for parental investments and the directly related maternal characteristic. Most effect sizes are very small and not statistically different from zero. In two cases, we even find a significantly negative relationship between maternal altruism and child patience and between maternal risk preferences and child altruism, respectively. However, given the large number of additional coefficients and small sample size, we are cautious to overinterpret these results.

Table B14: Production function with other maternal characteristics (average marginal effects)

| | Production function | | | |
|---|---|---|---|---|
| | IQ | Patience | Lower risk-taking | Altruism |
| **Marginal effects** | | | | |
| $\text{AME}_{M^l}$ | 0.584*** | 0.438*** | 0.251*** | 0.547*** |
| | (0.076) | (0.089) | (0.052) | (0.100) |
| $\text{AME}_{\text{Style}}$ | 0.319*** | 0.338*** | 0.421*** | 0.427*** |
| | (0.073) | (0.102) | (0.073) | (0.065) |
| $\text{AME}_{\text{Time}}$ | 0.367*** | 0.449*** | 0.620*** | 0.432*** |
| | (0.063) | (0.108) | (0.086) | (0.079) |
| $\text{AME}_{\text{Miq}}$ | | -0.001 | 0.006 | -0.073 |
| | | (0.038) | (0.055) | (0.046) |
| $\text{AME}_{\text{Mtime}}$ | -0.023 | | -0.023 | -0.034 |
| | (0.057) | | (0.055) | (0.061) |
| $\text{AME}_{\text{Mrisk}}$ | -0.024 | 0.023 | | -0.137** |
| | (0.053) | (0.067) | | (0.058) |
| $\text{AME}_{\text{Maltr}}$ | -0.030 | -0.119** | -0.051 | |
| | (0.046) | (0.050) | (0.053) | |
| Observations | 435 | 435 | 435 | 435 |

**Notes**: The reported SEs (in parentheses) were bootstrapped using 1,000 bootstrap replications. Significance stars at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In addition, it is conceivable that the productivity of the production process varies by ability, i.e., because high-IQ mothers have an easier time producing child preferences. To test this presumption, we introduce an IQ-specific productivity parameter $\Pi_{IQ}$ (in addition to $\Pi_{SES}$) to the model, to capture productivity differences that arise as maternal IQ lies above the median. The results of this exercise are displayed in table B15. $\Pi_{IQ}$ is close to and not significantly different from one in all instances. Hence, there are no apparent productivity differences between high and low IQ mothers.

Table B15: Production function with high IQ productivity parameter (productivity parameters and average marginal effects)

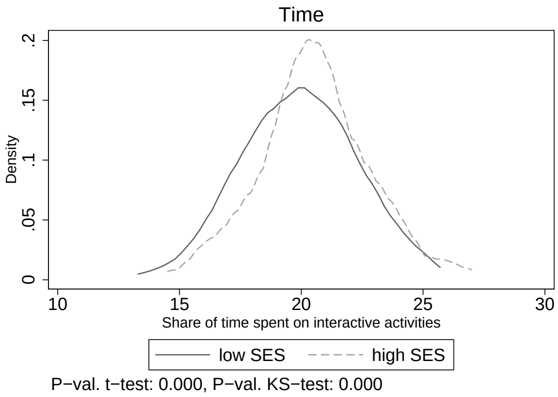
| | Production function | | |
|---|---|---|---|
| | Patience | Lower risk-taking | Altruism |
| **SES/IQ productivity** | | | |
| $\Pi_{SES}$ | 0.869 | 0.715 | 0.932 |
| | (0.103) | (0.081) | (0.105) |
| $\Pi_{IQ}$ | 0.987 | 0.983 | 0.996 |
| | (0.014) | (0.012) | (0.011) |
| **Marginal effects** | | | |
| $\text{AME}_{M^l}$ | 0.444*** | 0.251*** | 0.559*** |
| | (0.103) | (0.059) | (0.108) |
| $\text{AME}_{\text{Style}}$ | 0.342*** | 0.422*** | 0.417*** |
| | (0.090) | (0.071) | (0.064) |
| $\text{AME}_{\text{Time}}$ | 0.468*** | 0.620*** | 0.447*** |
| | (0.119) | (0.094) | (0.080) |
| Observations | 435 | 435 | 435 |

**Notes**: The reported SEs (in parentheses) were bootstrapped using 1,000 bootstrap replications. $\Pi_{IQ}$ is a productivity parameter that captures differences in the productivity of the production process for mothers with above-median intelligence. Significance stars at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

## B.16 Robustness check: alternative measure of parental time investments

In the main part of this paper, time investment is measured as the share rather than the level of "quality time." Using the share of highly interactive activities bears several advantages. First, it is less prone to reflect random differences in the total amount of time available to families in the past two weeks. Second, dividing by the overall number of activities takes out important systematic variation that is not explicitly modeled. Examples are single parent status, parental work arrangements and the possibility to rely on institutional childcare, such as after-school programs. Third, the share accounts for high SES mothers tending to substitute highly interactive activities for detrimental activities (Hsin and Felfe, 2014).

Figure B4: Parental Investments by Socio-economic Status




Yet, the level of time investment is arguably a plausible alternative measure, given ample evidence showing that high-SES parents tend to spend considerably more time on child rearing in total. Therefore, we reproduce our main results displayed in tables 1 and 3 of the main paper, but use the absolute number of highly interactive activities as an alternative measure of parental time investment. Moreover, we also include the overall number of joint activities as an additive covariate outside of the production function. The corresponding results are displayed in tables B16 and B17 below. While the results of the investment system (table B16) remain very similar, the gap in time investments is slightly smaller and there is more variability in the absolute number of interactive activities among low SES than among high SES families (see figure B4). Besides, the effect of the level of highly interactive activities on child outcomes is somewhat weaker (see table B17). Both in reduced form and structural analyses (see, e.g., the bottom of table B17), we find consistent evidence that it is not total time, but highly interactive time that matters for the development of child IQ and preferences (for related evidence along these lines, see Hsin and Felfe, 2014; Bono et al., 2016).

Table B16: The relationship between SES and parental investments (level of time)

| | Parental Investments | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Style | | Time | | Style | | Time | |
| **SES** | | | | | | | | |
| High SES | 0.230** | (0.091) | 0.402*** | (0.057) | | | | |
| Parental education | | | | | 0.020 | (0.020) | 0.071*** | (0.012) |
| Log HH income | | | | | 0.310*** | (0.117) | 0.118* | (0.068) |
| **Satisfaction child devt.** | | | | | | | | |
| $\delta_\alpha$ | 0.126*** | (0.033) | 0.024 | (0.021) | 0.121*** | (0.032) | 0.023 | (0.021) |
| Observations | 435 | | 435 | | 435 | | 435 | |

**Notes**: Standard errors (in parentheses) are bootstrapped using 1,000 bootstrap replications. Further control variables comprise maternal preferences and IQ, child age, the overall number of children in the household, an indicator of single parenthood, and the overall time parents and children spend together. Significance at * p < 0.1, ** p < 0.05, *** p < 0.01.

Table B17: Production function with level of time (average marginal effects)

| **Marginal effects** | **IQ** | **Patience** | **Lower risk-taking** | **Altruism** |
|---|---|---|---|---|
| $\text{AME}_{M^l}$ | 0.754*** | 0.264*** | 0.308*** | 0.552*** |
| | (0.085) | (0.035) | (0.074) | (0.114) |
| $\text{AME}_{\text{Style}}$ | 0.329*** | 0.188*** | 0.488*** | 0.439*** |
| | (0.069) | (0.032) | (0.090) | (0.124) |
| $\text{AME}_{\text{Time}}$ | 0.286*** | 0.143*** | 0.506*** | 0.277** |
| | (0.072) | (0.030) | (0.106) | (0.109) |
| $\text{AME}_{\text{Totaltime}}$ | −0.223*** | 0.064 | −0.118 | −0.183** |
| | (0.085) | (0.092) | (0.094) | (0.085) |
| Observations | 435 | 435 | 435 | 435 |

**Notes**: The reported SEs (in parentheses) were bootstrapped using 1,000 bootstrap replications. Total time enters the model as a control variable outside of the production function. Significance stars at * p < 0.1, ** p < 0.05, *** p < 0.01.