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The Economic Value of Childhood Socio-Emotional Skills

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Non-Technical summary

The rapid advancement of technology in recent years has profoundly changed the way we work. Many routine and even more complex tasks can now be performed using advanced technologies like robotics and Artificial Intelligence. This shift is leading to concerns about the loss of jobs and the need for workforce adaptation. To navigate this new employment landscape, it is crucial we understand what types of *human* skills provide a productivity advantage in labour markets.

Skills come in different forms, including cognitive and non-cognitive. Non-cognitive skills, often referred to as socio-emotional skills, encompass things like motivation, personality traits, and the ability to interact with others. A growing literature in economics and psychology investigates the development of these skills, especially in the early years, and points out that these skills can predict a wide range of outcomes in adulthood.

Our study focuses on the socio-emotional skills of individuals at age 10 and how they relate to their economic outcomes later in life using data from the 1970 British Cohort Study. We measure skills using information provided by teachers, who assess aspects such as attention, behaviour, and emotional regulation. By analyzing these data, we identify four key skill dimensions: attention, conduct, emotional, and relationship with peers.

We find that these socio-emotional skills are strongly linked to various adult outcomes, including earnings, work hours, and the types of jobs people end up in. Surprisingly, we discover that certain behaviours considered problematic in childhood, like conduct issues, are associated with higher earnings in adulthood. On the other hand, problems with attention, emotions, and peer relationships tend to lead to poorer labour market outcomes.

We also explore how these early skills might influence later outcomes through different pathways, such as career interests, socialization, and mental health. Although early skills are related to these mediating outcomes, we find that none of these pathways fully explain the relationship between childhood skills and adult economic success.

Several important policy relevant implications emerge from this analysis. Specifically, the result that child socio-emotional skills are predictive of a number of adult economic outcomes, even conditional on a range of confounders and mediators, provides strong support for policies and interventions that focus on the development of these skills in the early years. This clearly calls for integrating socio-emotional learning into the school curricula. Although this need is already recognized in the UK educational context, no uniform approach has emerged as yet.

Another consideration is that the positive association between conduct problems and labour market outcomes suggests a need to reconsider discipline policies in schools. It is possible that what is often identified as aggressive behaviour is the adaptive response to a competitive environment. Rather than a punitive approach, there could be more focus on understanding the causes of the disruptive behaviour and teachers could be trained to identify strategies that help children to channel these tendencies in ways that fit better with the classroom.

The Economic Value of Childhood Socio-Emotional Skills*

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Abstract

We investigate the relationship between child socio-emotional skills and labour market outcomes using longitudinal data from the 1970 British Cohort Study. We perform a novel factor analysis of child skills and capture four latent dimensions, representing 'attention', 'conduct', 'emotional', and 'peers' problems. Conditional on a range of confounding variables, we find that conduct problems, driven by aggression and impulsivity, are associated with positive outcomes in the labour market: higher wages, higher labour supply, sorting into 'good' jobs and higher productivity conditional on job tasks. Attention problems are instead negatively associated with labour market outcomes and this relationship is partially accounted for by schooling. We explore different mediating pathways, including through career interests, socialization and mental health - all measured in the adolescent period - but none of these is able to fully explain the association between child skills and later economic outcomes.

JEL Classification: J24, J62, I21.

Keywords: Socio-emotional Skills; Human Capital; Child Development; Labour Supply; Occupational Sorting.

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1 Introduction

The rapid development of new technologies in recent years has had far-reaching implications for the nature of work. Increasingly, routine and now also non-routine tasks can be performed by automated and autonomous systems, which make use of advanced technologies such as robotics and Artificial Intelligence. A rapidly growing economic literature examines the consequences that these changes have for employment, earnings, and the structure of occupations (Acemoglu & Restrepo, 2018, 2019; Autor, 2022) with some studies suggesting an increasing importance of socio-emotional skills as complements to these new technologies (Deming, 2017; Edin et al., 2022).

To examine these new developments, it is important to recognize that skills are multidimensional, encompassing cognitive and non-cognitive aspects (Heckman et al., 2006; Kautz et al., 2014). While there is no single or accepted definition of what non-cognitive skills are, it is generally understood that these skills include individual characteristics such as motivation, time preferences, personality traits, and the ability to relate to others (Heckman, 2008). Within this broad category, *socio-emotional skills* represent the capacity to regulate emotions and behaviours and have been shown to predict a wide range of adult outcomes (Goodman et al. 2015). These socio-emotional skills are of particular relevance to policy makers because evidence is accumulating on their malleability (Alan et al., 2021; Sorrenti et al., 2020). The literature, however, has not reached a consensus on which of these skills matter most in explaining labour market outcomes and what the possible mediating pathways might be.

In this paper we use data from the 1970 British Cohort Study (BCS70), a longitudinal survey which follows a cohort of children through their teen and adult years, to investigate how variation in early socio-emotional skills relates to later economic outcomes. Specifically, we measure individual skills at age 10 and consider their association with schooling, earnings, hours of work, and occupational sorting up to age 46. We then investigate various possible mediating pathways - including teen socialization, career interests, and mental health - by exploiting information gathered at age 16, just before the end of compulsory schooling.

Our first contribution is to present a comprehensive analysis of early socio-emotional skills as measured by teachers via different psychological instruments, including the Rutter Child Behaviour Questionnaire (Rutter, 1967), the Conners Hyperactivity Rating Scale (Conners, 1969), and the Swansea Assessment Battery (Butler et al., 1980). We include all available items from these batteries of questions in a detailed measurement system and, using exploratory factor analysis (as in Heckman et al., 2013 and Bolt et al., 2021), obtain a four-factor representation of skills. Specifically, our model captures 'attention' problems, which indicate difficulty in concentrating on a task and bear a strong connection with aspects of personality such as conscientiousness, 'conduct' problems, driven by aggression and impulsivity, 'emotional' problems, related to anxiety, and 'peer' problems, representing shyness and a difficulty forming friendships.

We show that our four factors are closely related to the main sub-scales of the Strengths and Difficulties Questionnaire (SDQ), one of the most commonly used screening tools for behavioural and emotional difficulties in children and young people (Goodman, 1997). The SDQ has become increasingly popular in social and economic longitudinal surveys; for example, it has been adopted in the UK Millenium Cohort Study (MCS) and the US Panel Study of Income Dynamics (PSID), but current data are only available for children or young adults.[1] In terms of longer-term outcomes, the SDQ has so far mainly been used in clinical studies, often based on convenience samples, to predict mental health disorders and other psychopathologies (Caye et al., 2016). To the best of our knowledge, our analysis is therefore the first to establish its association with a wider range of adult outcomes, including earnings, labour supply, and occupational choices in a representative sample of the population.

Our second contribution is to demonstrate that the relationship between early skills and adult outcomes is more complex than usually recognized. By extending our model to include a wider set of child behaviours and arriving at a four-factor representation of skills, we are better able to pin down the contribution of different skills to different economic outcomes. This distinguishes our study from previous work that emphasises the importance of a single skill (e.g. conscientiousness, Prevoo and ter Weel 2015), or favours a two-factor representation which separates broader constructs such as 'externalizing' and 'internalizing' behaviours (Attanasio et al., 2020; Papageorge et al., 2019). We are thus able to offer a richer and more nuanced characterization of the economic value of childhood skills.

Specifically, and most notably, we show that conduct problems are *positively* related to earnings. The effect is meaningful in terms of magnitude, indicating that a one standard deviation increase in conduct problems is associated with an increase in earnings of almost 4 percent.[2] This result is robust to the inclusion of a large range of confounders, including life-cycle earnings profiles, family socio-economic status, cognitive, and the other socio-emotional skills. This positive relationship is found to be equally strong for both males and females and is explained by higher wages as well as longer working hours. It also holds whether or not we control for attained years of schooling. Using data on occupational task intensities from O*NET, we show that the type of aggressive behaviours which define conduct problems are also strongly predictive of sorting into 'good' jobs - i.e. those that are intensive in analytical and interpersonal tasks. Yet, these behaviours predict higher wages even conditional on job task content.

[1] The SDQ has been collected from the PSID since 2019. Beyond the PSID and MCS (which represents children born in 2000 in the UK) it has been used in the Avon Longitudinal Study of Parents and Children (ALSPAC), which represents children born in the county of Avon (UK) in 1991-2, the UK Understanding Society (since 2011-12), the German Socio-Economic Panel (in an abbreviated version, since 2008), several Danish cohort studies (including children born from 1990 to 2002, see Niclasen et al., 2012), and in the Longitudinal Study of Australian Children (since 2008).

[2] By comparison, the effect of cognition is 6 percent and the effect of an additional year of schooling is just under 5 percent.

By contrast, problems of attention, emotion and with peers are predictive of negative labour market outcomes. Additionally, we find large negative effects for attention problems on schooling, especially for boys, as well as the ability to find good jobs. Specifically, a one standard deviation increase in attention reduces schooling by a little under three months (almost a third of the effect of cognition), and reduces earnings by almost 3 percent. Emotional problems, such as anxiety, lead instead to lower labour supply. Problems with peers are also associated with lower wages, although here the relationship is modest in magnitude.

The finding that certain behaviours that are considered problematic at school may lead to beneficial outcomes in the labour market is not new. In particular, Papageorge et al. (2019) point out that externalizing behaviours, which we show can be considered a mixture of attention and conduct problems, lead to better long-run labour market outcomes. This interpretation is also supported by studies that link competitive, or aggressive behaviour with success in entrepreneurial or high-stakes careers (see for example Levine & Rubinstein, 2017). They emphasize the fact that this relationship is observed even though externalizing behaviours predict lower schooling attainment. Our contribution on this front is to show that these apparently contrasting findings in terms of schooling and the labour market relate to different behavioural issues i.e. attention and conduct problems. This distinction is important when considering what schools can do to enhance socio-emotional skills.

Our third main contribution is to consider how the relationship between early skills and later economic outcomes may be mediated through several potential mechanisms. Here we use, among other sources of information, under-explored and detailed data on career interests that were collected when the respondents were aged 16, but that have only recently been processed and made available. We find that career interests, as well as socialization and mental health (also measured at age 16) matter for later outcomes, even conditional on early skills and the full range of background controls. We also show that these mediators have strong relationships with skills measured at age 10. For example, we observe a significant negative association between attention problems and interest in a business career, while emotional problems strongly predict mental health measured in adolescence. However, the main finding is that *none* of the mediators is able to explain the relationship between early skills and later labour market outcomes. It therefore appears that socio-emotional skills measured in childhood proxy adult abilities and competencies that are valued in economic terms but are not easily observed in our datasets.

Our results for conduct problems could be seen in the light of studies which have interpreted aggressive behaviour as an adaptive mechanism. This behaviour allows individuals to obtain the best possible outcome in certain situations, such as when competing for a partner or when negotiating status, thereby conferring an evolutionary advantage (Buss & Shackelford, 1997). Some recent papers propose this interpretation for some specific adolescent behaviours, such as bullying (Volk et al., 2022), which is one of the measures of conduct in our analysis and which has proved very difficult to tackle despite numerous interventions (Fraguas et al., 2021). Crucially, the evolutionary psychology perspective highlights that aggressive behaviours may confer an advantage in specific situations, while being generally detrimental in other contexts. In line with this hypothesis, we show that individuals who score high on conduct problems in childhood are more likely to drink, smoke, and engage in criminal behaviours later in life.

This work has implications for policies aimed at improving children's human capital. First of all, our findings provide strong support for policies and interventions which focus on the early years. This is because our analysis shows the long-term economic value of childhood skills even when a range of intermediate outcomes is taken into account. Secondly, our findings suggest that policies and interventions should target specific skills depending on the outcomes they want to improve. For example, if we want to increase educational attainment, our analysis shows that policy should focus on problems of attention, while conduct, emotional and peer problems appear to be less relevant. On the other hand, if we want to maximize labour productivity, we should recognize that some forms of aggressive behaviours might confer a significant premium.

After a review of the literature, the paper proceeds as follows. Section 3 discusses the data. Section 4 discusses the empirical methodologies. Section 5 discusses results of the factor analysis, before section 6 discusses the long-run outcomes of the childhood-measured skills. Finally section 7 concludes and discusses directions for further research.

2 Related literature

Our paper relates to several strands of the literature. First it relates to the large literature on the *economic returns to non-cognitive or socio-emotional skills*, broadly defined, that has blossomed over the last 20 years. The early papers in this literature draw mainly on personality psychology and focus on the relationship between personality traits and preferences parameters key to many economic models, such as time and risk preferences (Almlund et al., 2011; Borghans et al., 2008).[3] These studies address many important questions related to the measurement of personality traits, their stability across different contexts, and their development over time, but also show that personality traits help predict a range of adult outcomes, including education, earnings, and health. Like our study, most of these analyses are based on longitudinal cohort studies, which contain rich measures of child skills and adult outcomes. For example, Prevoo and ter Weel (2015) use BCS70 data to investigate the association between conscientiousness - one of the Big Five personality traits - and later life outcomes. While they focus mainly on conscientiousness, they explore the broader underlying structure of child skills using mother's reports on child behaviours at age 10 and 16,

[3] For earlier contributions, the seminal work of Heckman et al. (2006) analyses the effect on later outcomes of youth-measured skills aggregated into two dimensions: cognitive and non-cognitive. Their non-cognitive factor combines many of the elements analysed in further detail in the subsequent literature.

and (like us) argue for four underlying factors which they map into four personality traits.[4] Their findings suggest that conscientiousness - which is very much related to our 'attention' problems - is the psychological trait most consistently associated with labour market outcomes, whereas agreeableness - the opposite of our 'conduct' problems - shows no association with earnings although is sometimes positively related to employment and sorting in more skilled occupations.[5] Compared to these papers, we contribute by providing a rigorous exploratory factor analysis to arrive at the representation of skills.

More recently, most studies have abandoned the attempt to map measures of child behaviours onto personality traits, and use the available information for the purposes the questionnaires were originally intended to achieve. Accordingly, child skills are interpreted in terms of problems of emotional and behavioural regulation, and individual beliefs like self-esteem and locus of control. In this vein, Goodman et al. (2015) provide a comprehensive overview from across different UK cohort studies, examining associations between different measures of child socio-emotional skills and a variety of adult outcomes, but without adopting a formal measurement model. Specifically, for the BCS70 they use the mother's responses to the Rutter questionnaire at age 10 and frame early skills in terms of 'conscientiousness', 'conduct', 'emotional stability' and 'peer problems'. While their categorization of skills is similar to ours, in contrast to us they find that *good* conduct is important for later outcomes including educational attainment and earnings. More recently, Attanasio et al. (2020) derive a two-factor representation of early skills from a selected number of items of the BCS70 maternal Rutter questionnaire, identifying 'externalizing' and 'internalizing' aspects of behaviour and emotional regulation.[6] They study the evolution of these skills over childhood, using measures at age 5, 10 and 16, and show that their relationships with earnings at age 42 depend on when they are manifested. For example, they show that lower wages are predicted by externalizing problems at age 5, but not at age 16, when the same problem behaviour is positively associated to pay. Compared to Goodman et al. (2015) we provide an explicit factorization of skills. We improve on Attanasio et al. (2020) and related papers by exploiting a wider array of questions on child behaviour, showing their relevance, and relating the resulting factors to the sub-scales of the Strengths and Difficulties Questionnaire.

Another feature of some longitudinal surveys is that measures of childhood non-cognitive or socio-emotional skills are reported by different informants (or evaluators, or raters). These measurements may come from parents (usually mothers), teachers, independent observers, or even the child themselves.[7] Although they are strongly correlated, measures of childhood skills obtained

[4]They are unable to identify Openess in the OCEAN taxonomy of personality.

[5]Using the same data and the same factor representation as in Prevoo and ter Weel (2015), Wehner et al. (2016) construct a model of the production function of mental health that depends on the cost of effort which varies by personality traits, and find empirically that conscientiousness can reduce the strength of the relationship between emotional instability (measured at age 16) and later mental health outcomes.

[6]Externalising refers to deregulation of behaviour and internalising to problems in regulating emotions and mood.

[7]The idea of relying on multiple evaluators or multiple measurement methods has a long history in the broader psychometric and applied statistics fields (Campbell & Fiske, 1959; Joreskog, 1971).

from different informants are often shown to predict later outcomes quite differently.[8] In a recent study, Feng et al. (2022) compare child, guardian and teacher reports of child non-cognitive skills using data from a longitudinal survey of children in primary schools in the Mianzhu region of China. They document that teacher reports have the highest internal consistency and are better predictors of later children cognitive and behavioral outcomes in school. Closely related to our study, Papageorge et al. (2019) use teacher-reported measures of child socio-emotional skills from the National Child Development Study (NCDS) and document how misbehaviour at school is not necessarily indicative of poorer socio-emotional skills.[9] While we ultimately use reports from one source only (the teacher), we improve on the bulk of studies by incorporating mother-based reports into a multitrait-multimethod analysis, and so testing the validity of our factorization.

Second, our paper relates to a recent literature documenting and exploring *changes over time in the returns to skills*, and increases in the returns to socio-emotional skills in particular. Specifically, using multiple waves of the National Longitudinal Survey of Youth (NLSY), Weinberger (2014) shows an increase in the returns to the interaction between social and cognitive skills from the 1980s to the late 1990s. This result is replicated by Deming (2017) who extends the analysis to the 2000s and relates his findings to an increase in employment in jobs characterized by a higher importance of interpersonal tasks, as measured by O*NET descriptors, and a decline in jobs that are more intensive in cognitive tasks.[10] For the UK, similar findings are documented by Dickerson and Morris (2019) for the period between 2002 and 2016, and by Borghans et al. (2014) for the earlier decade in relation to changes in computer use. These findings have also motivated a small number of studies which model multidimensional matching between workers equipped with multiple skills and jobs that require different combination of those skills (see, in particular, Lindenlaub, 2017 and Lise and Postel-Vinay, 2020). Our study speaks to this branch of the literature by identifying the key dimensions of variation in skills among children, and how these relate to labour market outcomes.

Finally, in relation to the measurement of skills, our paper relates to work on the development of cognitive and non-cognitive skills, pioneered by Heckman et al. (2006) and further advanced in Cunha et al. (2010). Specifically, this study adopts a latent factor approach for the representation

[8]See the study by Johnston et al. (2014) who use the 2004 Survey of Mental Health of Children and Young People in Britain to examine the effects of child mental health on education outcomes. Del Bono et al. (2020) discuss the implication of relying only on mother's measurement of child non-cognitive skills for dynamic models of human capital development.

[9]It should be noted that even though reports from teachers may be more empirically relevant than reports from mothers for predicting labour market outcomes, the use of a single perspective should be treated with caution. This is nicely illustrated by Conti et al. (2014), who use *all* available measures of child behaviour in the BCS70 at age 10 - whether mother reported, teacher reported, or self-reported - and identify different latent factors, with some factors being mainly driven by maternal reports and others by teacher reports. The study shows that the relationship between early skills and later outcomes is sensitive to the measurement system used, which in turn determines the number and type of factors retained.

[10]See also Edin et al. (2022) for similar evidence from Sweden using data on military tests of personality for males aged 18.

of child skills, which are derived from a multiplicity of error-prone measures, and implements a 3-step measurement error procedure as in Heckman et al. (2013) and Bolt et al. (2021). As discussed above, we further investigate the convergent and discriminant validity of our four-factor model by performing a multitrait-multimethod analysis of teachers' and mothers' reports on child behaviours, following the main approach adopted in the psychometric literature (Campbell & Fiske, 1959; Goodman et al., 2010; Nunnally & Bernstein, 1994).

3 Data

3.1 BCS70

The British Cohort Survey 1970 is a study that follows the universe of around 17,000 individuals born in England, Scotland, and Wales during the second week of April 1970. Beyond collecting data during the perinatal period, these individuals have been surveyed in nine additional waves at ages 5, 10, 16, 26, 30, 34, 38, 42, and 46. At each of these ages, various forms of information were collected using methods such as tests, parent and teacher questionnaires, as well as self-reports.

Age-10 Skills: We make use of a wide variety of information available across the lifespan. At age 10, we exploit the 'Child's Social Behaviour' (Section B) and the 'Child's Development Behaviour' (Section C) sections of the Education Questionnaire, which was administered to the individuals' teachers.[11] These detailed questionnaires comprise 58 items from the Rutter Teacher Behavioural Scale, Conners Teachers Hyperactivity Rating Scale, and Swansea Assessment Battery (Rutter, 1967; Conners 1969; Chazan, 1980). They include questions on the extent to which the child, for example, 'is prone to daydreaming'. Teachers were asked to rate the responses on a scale from 'a great deal' to 'not at all', resulting in continuous data. The rationale for combining these scales was to augment the test of problem behaviour in the Rutter questionnaire, with more specific items on hyperactivity, that were the focus of the Conners and Swansea scales. To simplify the analysis and computation we remove items relating specifically to physical and motor skills, leaving 42 items. However, because social and interpersonal skills likely overlap significantly with cognitive skills, in addition to these questionnaires we also use the age-10 cognitive test battery administered to the child. For these we use the summed scores across eight areas, including reading and writing tests, the matrix test, and the verbal reasoning test.

In supplementary analyses, we investigate the role of mindset skills, particularly locus of control and self-esteem. For these we use additional scales, including the CARALOC scale (locus of control, Gammage, 1975) and the LAWSEQ scale (self-esteem, Lawrence, 1981). Here the child is the main respondent.

[11] For more information on the study see https://cls.ucl.ac.uk/cls-studies/1970-british-cohort-study. All questionnaires can be downloaded following the appropriate links. For example, the teacher questionnaire at age 10 is available at: https://cls.ucl.ac.uk/wp-content/uploads/2017/07/educat.pdf.

Background Characteristics: We make use of information on family socio-economic background, including: number of siblings, birth order, the presence of the father at birth, whether or not the mother was a teenager at the birth of the child, family income, parental employment and educational status.

Teen and Adult Outcomes: At age 16, we use data collected on skills and behaviours that reflect development during the teenage years. Specifically, we use seven relevant items from the 'Friends and Outside World' questionnaire and five items from 'Attitudinal Scale' to extract information on social attainment. To capture mental health during these formative years, we use the total score from the 22 questions of the Malaise Inventory, developed from the Cornell Medical Index Health Questionnaire (Brodman et al., 1951).

At age 16, we also use data from the JIIG-CAL Occupational Interests Questionnaire to capture attitudes towards work.[12] These data are particularly interesting and novel, as they were not included in the initial releases of the dataset and were only processed and publicly released in 2016. The questionnaire elicits attitudes by posing a sequence of 30 binary options for preferred occupational tasks, such as 'do engravings on glass' or 'arrange insurance for ships and airplanes.' A variety of option sequences were available, with the respondents able to select the most appropriate for their anticipated future skill level, such that those who expect to obtain a degree were given a menu of choices reflecting graduate-level jobs. For each pair, respondents were asked to choose one, neither, or both options. As such, the questionnaire captures overall enthusiasm for work as well as relative interests. We make use of a derived version of the data, using the Closs algorithm (Closs, 1978).[13] These capture career interests in the following domains: business occupations; practical; living; communication; art and caring occupations. Of these, we focus on *relative* career interests in business occupations as capturing an orientation to jobs that are highly paid, as we also control for total level of interest across all different tracks.

At later ages, we use information on completed education (at age 26), wages, hours of work, and three-digit occupational codes. We provide further details and descriptive statistics for all of these data in Appendix A. Table A.1 shows summary statistics for all the variables used in the analysis.

3.2 Data From O*NET

In addition to the information from BCS70, we also use data on the characteristics of the occupations in which the respondents work. In line with the literature we characterize these jobs according to the intensities of the tasks they require. To do this, we use data from US O*NET, which

[12] The full title of this questionnaire is 'Job Ideas and Information Generator Computer-Assisted Learning'.
[13] See the discussion of this algorithm in Dodgeon et al (2016).

has been converted to the UK occupational classifications by Jin (2022) and Dickerson and Morris (2019).

Using the approach of Lise and Postel-Vinay (2020), we reduce O*NET descriptors to three dimensions 'Analytical', 'Physical', and 'Interpersonal'. We run a principal component analysis on the importance scores of over 200 O*NET descriptors from the Skills, Abilities, Knowledge, Work Context and Work Activities categories (see Appendix A) and keep the first three principal components, which capture around 70% of the total variance. We combine these principal components to estimate task requirements that satisfy the following exclusion restrictions: Analytical tasks are given by mathematics skills, physical tasks are given by mechanical knowledge and interpersonal tasks are given by social perceptiveness skills. As examples of the estimated intensities, occupations scoring highest on both analytic and interpersonal are 'Chief Executives and Senior Officials', 'Health and Social Services Managers and Directors', etc. Occupations scoring highest on physical are 'Construction Operatives', 'Plant and Machine Operatives', etc.

3.3 Sample

As previously stated, our approach involves using an unusually wide variety of data for each individual, incorporating hundreds of questions and test items. However, this approach poses a main problem that many of the single question items may be missing. We address this by discarding individuals with more than one missing item per scale. For the remaining individuals, we impute the single missing item if necessary, using a random forest model. For the age-10 items, the degree of imputation is modest. For example, for the age-10 cognitive tests, we have over 11,000 complete responses and need to impute only around 360 additional test items. Our imputation approach is most intensively employed on the age-16 items, such as Friends & Outside World questionnaire, for which we have around 4,300 complete responses, but impute missing items for an additional 2,000 individuals. We provide more detailed information on the imputation and present validation statistics in Appendix A, Table A.3.

Our main sample is constructed as follows: We start with 14,870 individuals for whom there is information at age 10. To permit a consistent analysis we remove those for whom there is no labour-market information at any age. After removing these individuals and those with multiple missing items in each of the relevant scales, we are left with data on 6,952 individuals, with 23,451 individual-year observations. When including the information collected at age 16, our sample is more limited: When including information on socialization, the sample is reduced to 3,288; when including information on both socialization and occupational interests, the sample is further reduced to 1,847. Throughout the analysis, when presenting results from different specifications we use unified samples for comparability of results. This sampling information is presented in Table A.2.

4 Methodology

4.1 Factorization

Following the recent economic literature on child development, we interpret the items in our dataset as multiple measurements of latent unobserved factors. Using the machinery of factor analysis to use these data has several attractive properties. Primarily, in terms of our main objective, it allows us to address the important conceptual question of assessing by how many dimensions, and in what way, individuals differ. Second, in terms of examining long-run outcomes, it allows us to reduce hundreds of potential explanatory items for each individual to a small set. Finally, given that each of the singular items is measured with noise, this approach provides a practical way to deal with measurement error. Our analysis follows the approach of Heckman et al. (2013) and Bolt et al. (2021), and uses similar notation. Here we provide an overview of the main steps and ideas, and refer the reader to these preceding papers for detailed arguments.

To proceed, and assuming that our items are measured on a continuous scale and are standardized, we use the following model:

$$Z_{\omega,i,j} = \lambda_{\omega,j}\omega_i + \epsilon_{\omega,i,j} \tag{1}$$

where $Z_{\omega,i,j}$ is the response to item j for individual i and for latent factor ω; $\lambda_{\omega,j}$ is the loading on item j for factor ω, which has mean zero; ω_i is individual i's level of this factor, and $\epsilon_{\omega,i,j}$ is a mean-zero measurement error.

This model leaves the precise number of factors and the assignment of items to factors unspecified, and to be determined empirically. To achieve identification, and as standard, we impose $Cov(\epsilon_{\omega,j}, \epsilon_{\omega,j'}) = Cov(\omega, \epsilon_{\omega,j}) = 0$ for items $j \neq j'$, and $Var(\omega) = 1$.

The first challenge, therefore, is to determine the number of factors and the item assignment. We proceed with a dedicated exploratory factor analysis (EFA), following, for example, Heckman et al. (2013). To make the analysis manageable, we group the items into three broad domains: cognitive and socio-interpersonal skills; family background, and teen (age-16) socialization. We then follow an iterative process as follows: we perform a first exploratory factor analysis using all items, and then successively remove items either with factor loadings below 0.4, or which have high loadings on multiple factors - specifically with a ratio of loadings greater than 75%. Meanwhile, the number of factors is chosen using the Kaiser criterion. The process terminates at the round when no further items and no factors are dropped. This method results in a system where each factor is aligned with a specific set of items. Accordingly the empirical content of each factor is highly transparent.

To assess model fit and to analyse long-run outcomes, following the EFA we estimate the final factor system using a dedicated confirmatory factor analysis (CFA), setting all cross loadings to zero. We subsequently estimate factors at the individual level using Bartlett scores. These aggregate item scores, $Z_{\omega,i,j}$, as follows:

$$\omega_i^S = \kappa_\omega \sum_j \frac{\lambda_{w,j}}{\sigma^2_{\omega,\epsilon,j}} Z_{\omega,i,j} \tag{2}$$

where $\sigma^2_{\omega,\epsilon,j}$ is the variance of the noise on the jth item, equalling $1 - \lambda^2_{w,j}$, $\kappa_\omega \equiv \left(\sum_j \frac{\lambda^2_{w,j}}{\sigma^2_{\omega,\epsilon,j}} \right)^{-1}$ is a factor-specific scaling factor, and all components can be replaced with sample counterparts. These factor scores can be construed as the coefficient from a (weighted) regression of the item scores on the loading factors at the individual level, and minimize noise among scoring methods.

4.2 Long-term Outcomes

A general form for modelling most of our key long-term outcomes is expressible with the following linear specification:

$$y_{i,t} = \Gamma \Omega_{i,\langle a \rangle} + \beta^l X^l_{i,t} + \beta^f X^f_i + v_{i,t} \tag{3}$$

where y is the outcome of interest (such as earnings, wages or hours) for individual i measured at age t, Ω captures the vector of skills measured at age $\langle a \rangle$ (age 10 and/or age 16), X^f captures other confounding variables related to family background, and $X^l_{i,t}$ captures contemporaneous variables from adulthood. In terms of these adult covariates, we control flexibly for differential life-cycle profiles for earnings by running an interaction of age (year-of-interview) with gender and with marital status.[14]

There remains the problem that $\Omega_{i,\langle a \rangle}$ is not observed directly. However given the factor structure above we can replace this vector with the noisy factor scores from (2). We are then left with a linear errors-in-variables model where the signal-to-noise ratio can be directly estimated. We therefore proceed by running regressions with the noisy scores and scaling by an estimable bias-correction factor as standard. We specify the precise formulation of the bias correction in our case, as derived by Heckman et al. (2013), in Appendix A.

We cluster standard errors at the individual level, allowing for components of earnings that are serially correlated across years and that are not picked up by the main model features.

5 Factorization Results

As discussed in section 4, we use an iterative exploratory factor analysis (EFA) to assess dimensionality and search for a system of dedicated measures for each factor. Our main focus is on age-10 skills. We then perform separate analyses for family background, and age-16 socialization.

[14] We explored the role of well-known differential life-cycle profiles by education by also controlling for the interaction of education with age; results were little changed.

Age-10 Skills

At age 10 we start with a total of 50 items comprising eight cognitive test scores and 42 measures from the sections of the Education Questionnaire devoted to child behaviour.[15] After iterating the factorization and dropping irrelevant items, we retain five factors with adjusted eigenvalues equal to or larger than one. To further validate our procedure and the number of factors we eventually retain, Appendix Figure B.1 shows a scree plot of the first six eigenvalues from the final EFA iteration, together with the adjusted eigenvalues from Horn's parallel analysis.[16]

Table 1 shows results from the first round of EFA after oblique rotation of the loading matrix, which we use to show the performance of all the items in detail. Drawing some initial parallels with the modern Strength and Difficulties Questionnaire (SDQ), which we develop and discuss throughout this section, we label the socio-emotional factors as relating to problems of: 'attention', 'conduct', 'emotion' and 'peer', with higher scores indicating more problems and lower regulation skills. The final factor we label 'cognition'. As discussed in section 4, following Heckman et al. (2013) and Bolt et al. (2021), we do not retain measures with loadings below 0.4 as these are considered to be unstable. Measures that do not survive the procedure are shown in plain (non-bold) font. Examples include 'cannot negotiate child's behaviour' and 'face or body twitches'. As we are using a dedicated measurement system, we also do not retain items that cross-load too highly between two or more factors such as 'child is squirmy and fidgety' and 'child confused with difficult tasks'. Overall we drop 8 of the 50 items. The bottom row shows that Cronbach's alpha is well above 0.8 for all the factors, indicating high internal consistency of all the factors identified by the model.

To ensure a consistent set of items for all individuals, we perform the EFA pooling across men and women. To check that our approach picks up the same factors across genders, we show the final iteration of a gender-specific EFA in Table B.1, which reports the full set of loadings across all factors for the final set of items. As one can see, the loadings are very similar by gender, and the internal consistency (measured by the Cronbach's alpha) remains above 0.8 for all the factors even when using the smaller samples for men and women separately.

As discussed, our factorization relates closely to the scales from the SDQ (Goodman, 1997). However, there are small differences due to the presence or absence of various items, and small variations in the wording of items in common. We show the correspondence in Appendix Table B.2. Here we mainly see some differences in relation to our first factor (attention). Several items that match the SDQ's hyperactivity scale (such as 'easily distracted') load on this factor, but other items that align with hyperactivity in the SDQ load instead on conduct in our model (such as

[15] As discussed previously, in a prior step we exclude 16 items related to fine motor skills, particularly hand-eye coordination.

[16] Parallel analysis, as suggested by Horn (1965) is another approach to determine the number of latent factors, and is still considered one of the most valid methods to determine factor dimensionality (Lim and Jahng 2019).

Table 1: Explanatory Factor Analysis (EFA) of Age-10 Skills: First Iteration

Items	**Attention Problems**	**Conduct Problems**	**Emotion Problems**	**Peer Problems**	**Cognition**
Easily distracted	**0.793**	0.137	0.029	-0.116	-0.043
Fails to finish tasks	**0.783**	-0.033	-0.029	0.064	-0.006
Cannot complete tasks	**0.773**	-0.050	-0.058	0.072	-0.030
Fails to pay attention in class	**0.725**	0.056	-0.086	0.069	-0.095
Fails to show perseverance	**0.722**	0.023	-0.062	0.060	-0.084
Bored in class	**0.690**	0.159	-0.018	0.074	-0.022
Daydreaming	**0.671**	-0.128	0.112	0.124	0.022
Forgetful on complex task	**0.611**	-0.039	0.211	-0.010	-0.203
Cannot concentrate on task	**0.584**	0.004	0.041	0.027	-0.082
Squirmy and fidgety	0.543	0.388	0.122	-0.183	0.039
Shows lethargic behaviour	**0.493**	-0.020	0.138	0.290	0.001
Confused with diffic. tasks	0.457	-0.085	0.388	-0.031	-0.266
Displays outbursts of temper	-0.053	**0.798**	0.037	0.068	-0.030
Teases other children	0.030	**0.783**	-0.125	0.013	-0.036
Bullies other children	-0.025	**0.781**	-0.137	0.101	-0.073
Quarrels with other kids	0.041	**0.759**	-0.005	0.141	-0.079
Changes mood quickly	0.024	**0.701**	0.253	-0.011	-0.014
Interferes with others	0.289	**0.643**	-0.104	-0.022	-0.026
Complains about things	0.052	**0.623**	0.125	0.020	-0.030
Sullen or sulky	0.015	**0.623**	0.101	0.255	-0.039
Destroys belongings	0.099	**0.609**	-0.046	0.142	-0.013
Excitable and impulsive	0.124	**0.597**	0.217	-0.345	0.023
Restless or over-active behv.	0.295	**0.554**	0.215	-0.247	0.056
Easily frustrated	0.164	**0.526**	0.207	-0.068	-0.017
Hums or makes odd vocals	0.277	**0.436**	0.012	-0.043	0.048
Rhythmic tapping in class	0.289	**0.419**	0.037	-0.056	0.056
Cannot negotiate child's behv.	0.281	0.316	-0.126	0.278	0.042
Face or body twitches	0.115	0.251	0.199	0.019	0.045
Worried	0.000	0.061	**0.829**	0.005	-0.013
Behaves nervously	0.127	-0.055	**0.719**	0.073	-0.033
Anxious	-0.037	-0.024	**0.699**	0.182	-0.031
Fussy	-0.093	0.300	**0.564**	-0.050	0.043
Afraid of new situations	0.162	-0.177	**0.560**	0.103	-0.172
Obsessed with unimportant tasks	0.015	0.377	0.447	0.050	0.003
Cries for little cause	-0.048	0.333	0.416	0.087	-0.042
Unhappy or tearful	-0.012	0.355	0.371	0.351	-0.006
Child is not friendly	0.141	0.172	0.057	**0.719**	-0.035
Child is not popular with peers	0.160	0.227	0.028	**0.698**	-0.043
Introvert	-0.035	-0.316	0.297	**0.606**	-0.005
Rather solitary	0.017	0.047	0.243	**0.549**	0.100
Child is not cooperative	0.147	0.365	-0.046	**0.538**	-0.026
Child is not bold	0.016	-0.434	0.333	0.450	-0.069
BAS words	0.094	-0.025	0.008	-0.001	**0.806**
Reading	-0.113	-0.006	0.024	0.015	**0.800**
Maths	-0.087	0.012	-0.017	0.006	**0.776**
Pictorial (PLC)	0.109	-0.059	-0.001	0.018	**0.773**
BAS simil	0.089	-0.019	-0.006	0.015	**0.760**
BAS matrix	-0.053	-0.043	0.032	0.018	**0.629**
Spelling	-0.230	0.065	-0.010	0.011	**0.545**
BAS digits	-0.074	0.029	-0.022	0.009	**0.420**
Cronbach's alpha	0.9246	0.9314	0.8469	0.8233	0.8558

Notes: Data from BCS70. The table reports factor loadings obtained from an exploratory factor analysis (EFA) of the main sample (6952 observations) using a polychoric correlation matrix and oblique quartimin rotation. Items in bold are subsequently retained after several iterations and used in our dedicated measurement system. The items not in bold are dropped. Cronbach's alpha coefficients for the internal consistency of the set of retained items within each factor are also reported.

‘excitable’). For this reason we give our first factor a different label: ‘(problems of) attention’. Otherwise, the scales line up closely, and the SDQ conduct, emotion and peer problem dimensions match to our equivalent factors. As a final point, our question list includes one item (‘child is not cooperative’) that is most similar to the SDQ item ‘volunteers to help others’, and which appears in the SDQ pro-social scale. We find that this item fits reliably into our factor capturing peer problems.

Our finding of four factors capturing socio-emotional skills differs from several recent papers in economics, which, using the Rutter questionnaire only, find two factors, typically labelled ‘externalizing’ and ‘internalizing’ (see, for example, Attanasio et al., 2018; Papageorge et al., 2019). To investigate the relationship of our factors with this two-factor structure we perform a factorization using only the Rutter items and find, consistently with these studies, that only two factors are retained. Results from the final EFA for these Rutter items is presented in Appendix Table B.3 which shows the loadings and also how the resulting factors align with our preferred factorization. Here we see that the items in externalizing mostly line up with conduct, with one item (‘squirmy and fidgety’) that is more aligned with attention, and that those in internalizing line up with emotional and with peer problems. However, it is worth remarking that the overlap is not perfect: three of the items that are retained (‘squirmy and fidgety’, ‘face or body twitches’ and ‘unhappy or tearful’) are ultimately not retained in our analysis.

We investigate the validity of our factorization formally, and in further detail, by following Goodman et al. (2010) and performing a multitrait-multimethod analysis of our factorization. This analysis uses the fact that a subset of items were collected from both teachers and also mothers. The approach here is to test convergent and discriminant validity of our factor structure by looking at the correlation of estimated factor scores across both traits *and* informants. The idea is that, if the basic constructs are valid, then both mother and teacher should be assessing the child along the same dimensions. Accordingly, the correlation of, say, conduct measures estimated from mother and from teacher reports should be high (convergent validity), while the correlation of, say, conduct measured from the mother with peer problems measured by the teacher should be lower (discriminant validity). To perform this exercise, and analogously with Goodman et al., we take the raw sum of the items from our main factorization shown in Table 1. Where an item is not included in the mother questionnaire we exclude it from the sum calculated for the teacher.

The results of this exercise are shown in Appendix Table B.4. The bottom left-hand block reports the relevant cross-correlations, which shows that in most cases the diagonal element is indeed higher than the off-diagonal elements. The right-hand column of the table shows formal tests of the marginal cases, which are the cross correlations of attention and conduct and of emotion and peer problems. Similar to the analysis of SDQ subscales in Goodman et al. (2010), we see weaker discriminant validity between conduct and attention problems. However, this is not specific to our analysis, and is highlighted also in the test performed by Goodman et al. as a more general problem in relation to the SDQ conduct and hyperactivity scales. As in their study, we also find that a more detailed factorization performs better in terms of goodness of fit than the coarser factorization into externalizing and internalizing.

Finally, we investigate the relevance of additional aspects of child development, by expanding our analysis and performing analogous analyses including 16 items from the Child Locus of Control (CARALOC) questionnaire and 12 items from Lawrence Self-Esteem (LAWSEQ) questionnaire. We display the results from an initial EFA which includes these in Table B.5, and which shows that neither scale convincingly suggests the presence of an additional factor. For locus of control, most of the items are not retained because of weak loading.[17] When adding self-esteem items, an additional factor is in fact added to our five-factor system. This comprises eight reverse coded items such as 'nobody to play with at school' and 'children break friends or fall out with you'. However, the Cronbach's alpha for this factor is relatively small compared to the others at just above 0.7, and this becomes even weaker when splitting the sample by gender (not shown). Thus, our preferred measurement system is given by the five-factor specification, although we show additional results including self-esteem in Appendix C.

Family Socio-Economic Status and Age-16 Socialization

We perform a separate factorization for questions about family socioeconomic status such as parental education, parental employment and family income. As shown in Appendix Table B.6, all these items have loadings greater than 0.6 and are captured by a single factor with an eigenvalue of 2.1 which accounts for approximately 60% of the total variance.

To capture socialization at age 16, we use information from both the 'Friends and Outside the World' questionnaire and 'Attitudinal Scales'. The former provides information on the social behaviour of the teenager during school term such as 'spend time at friend's homes' and 'go out with friends do nothing special'. The latter shows analogous measures of social behaviour during leisure time. We select 12 items including the number of friends in and outside school, and drop 4 items that load poorly. The first-round EFA for the age-16 characteristics is also shown in Appendix Table B.6.

Confirmatory Factor Analysis and Raw Correlations

We use a dedicated measurement system as described in equation (1) to perform a Confirmatory Factor Analysis (CFA). As the sample decreases dramatically when using information at age 16, we run CFA for the full sample (excluding age-16 items) and the smaller sample (including social behaviour) separately. The final loadings for each of these samples are given in Appendix Tables

[17] Several questions within the CARALOC questionnaire, particularly those related to school performance load in the cognitive factor such as 'surprise when teacher says done well', 'high marks is a matter of luck', 'test are a lot of guess work', etc. After several iterations, there is only one item retained from this questionnaire, 'blamed when it is not your fault', which loads highly with other items from the LAWSEQ scale.

B.7 and B.8, which show that the weights are similar across samples. These tables also show various goodness of fit tests, including the Tucker-Lewis Index and Comparative Fit Index, which overall indicate good model performance. From the main CFA we extract six Bartlett-corrected factor scores (one cognitive, four behavioural and one family ses) as given by equation (2). From the CFA using the additional age-16 data we extract seven factor scores including the extra factor related to teen social behaviour.

Looking now at the estimated factors, Appendix Table B.9 shows the correlation matrix of the raw factor scores, together with additional relevant variables of interest. These are computed using the narrower sample including measures at age 16. Looking at the bottom of the table, years of schooling correlates positively and strongly with cognition and family socio-economic status, and negatively with the four socio-emotional problem behaviours of interest. The factor representing cognitive skills is moderately negatively correlated with attention problems and weakly negatively correlated with the other three behaviours. The four socio-emotional problem behaviours themselves are positively correlated, with the strongest pairwise relationship between attention and conduct problems. Teen socialization is weakly related to all the other variables on these univariate comparisons, although, not surprisingly, its strongest correlation in absolute terms is with age-10 peer problems.

Table B.9 also displays correlations with scores from the alternative factorization into externalizing and internalizing behaviours. As expected, externalizing correlates most strongly with conduct, less strongly with attention, and only mildly with emotional and peer problems. Internalizing correlates most strongly with emotional problems, less strongly with peer problems and moderately with attention and conduct. In a multi-variate context (not shown), when we partial out the role of other factors, attention and conduct have no extra explanatory power for internalizing behaviours beyond emotional and peer problems, while, in parallel, emotion and peer have no explanatory power for externalizing after controlling for attention and conduct.

6 Results on Long-Run Outcomes

Having established a factorization based on four socio-emotional skills, and shown their alignment with the SDQ scales, we now explore the relationship between these skills and later outcomes. Given that the estimated number of skills is relatively high, we streamline the discussion by synthesizing the results and only discussing the key relationships that we find.

6.1 Basic Relationship With Key Labour-Market Outcomes

Table 2 shows the relationship between childhood behaviours measured at age 10 and earnings, along with key confounding characteristics and additional background controls. The first column

Table 2: Determinants of Earnings

	All			Males	Females	q-values
	[1]	[2]	[3]	[4]	[5]	[4]-[5]
Attention	-0.092***	-0.037***	-0.027***	-0.024**	-0.036**	0.501
	[0.008]	[0.009]	[0.009]	[0.010]	[0.014]	
Conduct	0.052***	0.035***	0.037***	0.027***	0.046***	0.134
	[0.007]	[0.007]	[0.006]	[0.008]	[0.011]	
Emotion	-0.032***	-0.028***	-0.029***	-0.025***	-0.029***	0.720
	[0.007]	[0.007]	[0.006]	[0.008]	[0.010]	
Peer	-0.010	-0.011	-0.014**	-0.030***	0.005	0.011
	[0.007]	[0.007]	[0.007]	[0.009]	[0.010]	
Cognition		0.093***	0.060***	0.060***	0.077***	0.025
		[0.007]	[0.007]	[0.010]	[0.012]	
Family SES	0.107***	0.075***	0.046***	0.043***	0.026**	0.013
	[0.007]	[0.007]	[0.007]	[0.010]	[0.010]	
Yrs School			0.049***	0.027***	0.075***	0.000
			[0.003]	[0.003]	[0.005]	
Backg. Controls	X	X	X	X	X	
N	6952	6952	6952	3386	3566	
Individual-years	23,451	23,451	23,451	11,404	12,047	

Notes: Data from BCS70. Each column reports measurement-error-corrected estimates from a regression of the log real monthly earnings on standardized socio-emotional skills, cognition, and family socio-economic status obtained from our dedicated measurement system, see equation (1). All specifications control for: number of siblings, dummies for first child, no dad at birth, teenage mother, year and region fixed effects. Specifications [1] to [3] also include controls for gender and gender-by-year. Standard errors in brackets are estimated from 250 bootstrap replications clustered at the individual level: ***p < .01, **p < .05, *p < .10. FDR q-values are p-values of gender differences adjusted for multiple hypothesis testing at outcomes of interest. For the socio-emotional skills q-values, tests are grouped across the four skills and across five outcomes: years of schooling, earnings, wages, hours and tasks. For cognition q-values, family SES and years of schooling, each characteristic is treated separately but again across the five outcomes of interest.

shows the relationship between these age-10 characteristics, controlling only for the life-cycle profile of earnings and family socio-economic status, but not for cognition or years of education.

Similarly to Prevoo and ter Weel (2015), the data show a strong negative relationship between problems of attention (which can be equated to 'low conscientiousness') and earnings: Moving from two standard deviations below the mean for this behaviour to two standard deviations above is associated with a decrease in earnings of 37 log points, or around 45%.[18]

The next row shows the most striking result from this table. Echoing the findings in Papageorge et al. (2019), bad conduct is associated with strong *positive* effects on earnings. As we shall

[18] In terms of causal evidence, Alan et al. (2019) implement an intervention on the closely related concept of grit in Turkey which shows strong effects on cognitive achievement. Sorrenti et al. (2020) also use an early-years intervention in Germany to reduce impulsivity and disruptive behaviour and then educational outcomes.

see later, this finding remains robust even with the addition of extra controls, and so is worth remarking on here. We explain this result by noting that problems with conduct most saliently include aggression, which in later life has consistently been found to relate to positive returns in the labour market.[19]

Moving on to the remaining behavioural skills, and consistent with earlier studies, emotional problems are negatively associated with earnings, conditional on the other behavioural factors. Finally, in this initial analysis, peer problems seem to have no noticeable relationship with earnings.

This picture changes somewhat when we control for cognitive ability. This characteristic has a strong association with earnings: a one-standard deviation increase in cognitive ability is associated with around 10% higher earnings. More relevantly, including it in the controls modifies the observed relationship between earnings and behavioural skills. Most notably, the coefficient on attention, which is strongly negatively correlated with cognitive test scores, is reduced by around 60%. Similarly, the coefficients on conduct and emotional problems are reduced, although they remain strongly significantly different from zero.

In the third column, we control for a potentially mediating outcome which is determined between age 10 and earnings: attained years of schooling. As expected, schooling itself has a strong association with earnings, and controlling for its effect modifies the other relationships. Given the strong positive correlations between schooling and cognitive scores and background family SES (including parental education), the coefficient on these latter two characteristics are reduced substantially. In terms of the variables of our focus, the coefficient on attention problems is brought down further still. Now moving from two standard deviations below the mean to two standard deviations above is associated with a decrease in earnings of only around 12%, though this is still a non-negligible effect. The coefficients on conduct and emotional problems, by contrast, remain similar to those seen in the second column.

When controlling for all of schooling, cognition and family background, the coefficient on peer problems becomes significant at the 5% level. In fact, increased education compensates (or negatively mediates) the apparent negative effect of peer problems slightly: Holding fixed years of schooling therefore *increases* the apparent negative costs of this characteristic. In this case, this compensation effect is small however.

Overall, the message from the first three columns of Table 2 is clear and strong: behaviours that are deemed negative in terms of attentiveness, emotional stability and ability to form relationships with peers have negative associations with long-term labour market prospects, while aggressive conduct has apparent positive effects.

[19] See, for example, Almlund et al. (2011). In more detail, these behaviours are associated with reduced agreeableness in adulthood, which correlates negatively with labour market outcomes across a range of measures.

In the right hand side of Table 2, we begin to explore differences in the effects of these age-10 skills by gender. Looking at the standard measures of human capital, we see that the effects of schooling and cognition seem strikingly stronger for girls, a finding seen elsewhere in the literature. To test this formally, the final column of the table shows 'q-values' on these gender differences, computed using the method as in Benjamini et al. (2006) and Anderson (2008). These q-values are the equivalent of p-values, but allow for multiple hypothesis testing.[20] For these two measures of skill, the q-values, which provide conservative tests, indicate that gender differences are indeed significant. In the case of schooling, the difference is strong. Moving on to the age-10 behavioral skills, the only interesting gender difference arises in the case of peer problems. Here, the negative consequences are significantly and quantitatively strong for boys but not girls.

We explore the results from Table 2 further by breaking down log earnings into log wages and log hours of work. It should be remembered here that these results are for those reporting positive earnings and so only examine differences in hours along the intensive margin. Briefly, when looking at wages, Table 3 shows that the associations with childhood skills and schooling outcomes are of the same sign as for earnings. Perhaps the most noticeable difference for the first three columns is that the negative effect of emotional problems is much smaller compared to that shown in Table 2, indicating that the negative effect of, for example, anxiety operates partly through reduced labour supply. In terms of gender differences, the effect of peer problems is negative and significant for both *both* boys and girls, with no significant difference between the two groups.

The results for hours are shown in Appendix Table C.1. Part of the extra returns to earnings due to schooling and cognition for girls is due to significantly higher labour supply. In terms of the factors of interest, the socio-emotional skills measured at age 10, the coefficient for conduct problems is positive and indicates more hours of work, everything else equal. This table also confirms that both genders who exhibit emotional problems show reduced labour supply, with a stronger effect for girls. However, the starkest gender difference in the association between skills and hours appears for peer problems, which have a *negative* coefficient for boys, but a *positive* one for girls. The extent to which these gender differences in outcomes are driven by differences in family composition and fertility choices is not something we explore further here.

Table C.2 displays results at the extensive margin, and shows that effects compared to the intensive margin are subtly different.[21] Overall, attention problems lead to noticeably *lower* engagement

[20] We compute the q-values by combining hypotheses across the four socio-emotional skills of interests and across the following primary outcomes: years of schooling, earnings, wages, working hours and occupational tasks. We take multiple hypotheses into account when testing gender differences because only a fraction of differences appear significantly different, and so it is important to mitigate false discoveries.

[21] It is worth noting that the model reported in Table C.2 includes as being in work both employees and the self-employed. The rest of our analysis looks at employees only. When we repeat Table C.2 but excluding the self-employed, results are similar. Also, to emphasize, our main results for earnings shown in Table 2 condition on positive labour supply only.

Table 3: Determinants of Wages

	All			Males	Females	q-values
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[4]-[5]**
Attention	-0.081***	-0.036***	-0.028***	-0.026***	-0.032***	0.683
	[0.006]	[0.007]	[0.007]	[0.009]	[0.010]	
Conduct	0.039***	0.025***	0.026***	0.019***	0.033***	0.175
	[0.005]	[0.005]	[0.005]	[0.007]	[0.007]	
Emotion	-0.014***	-0.011**	-0.012**	-0.018**	-0.005	0.205
	[0.005]	[0.005]	[0.005]	[0.007]	[0.007]	
Peer	-0.015***	-0.016***	-0.018***	-0.023***	-0.012*	0.327
	[0.006]	[0.006]	[0.005]	[0.008]	[0.007]	
Cognition		0.077***	0.051***	0.048***	0.054***	0.625
		[0.006]	[0.006]	[0.010]	[0.008]	
Family SES	0.094***	0.068***	0.037***	0.053***	0.035***	0.108
	[0.005]	[0.005]	[0.002]	[0.009]	[0.007]	
Yrs School			0.045***	0.028***	0.048***	0.000
			[0.006]	[0.003]	[0.003]	
Backg. Controls	X	X	X	X	X	
N	6952	6952	6952	3386	3566	
Individual-years	23,451	23,451	23,451	11,404	12,047	

Notes: Data from BCS70. Each column reports measurement-error-corrected estimates from a regression of the log real hourly wage on standardized socio-emotional skills, cognition, and family SES obtained from our dedicated measurement system, see equation (1). All specifications control for number of siblings, dummies for first child, no dad at birth, teenage mother, year and region fixed effects. Specifications [1] to [3] also include controls for gender and gender-by-year. Standard errors in brackets are estimated from 250 bootstrap replications clustered at the individual level: ***p < .01, **p < .05, *p < .10. FDR q-values are adjusted p-values of gender differences for multiple hypothesis testing at outcomes of interest: See notes to Table 2 for details.

with the labour market, with the effect concentrated on females. As at the intensive margin, bad conducted is associated with increased labour supply for females. However, interestingly, for boys the effect is reversed and labour supply at the extensive margin is in fact lower. This last finding indicates some of the complexity of the relationship of conduct with adult outcomes that we explore further throughout this section.

In terms of the other skills, associations for emotional and peer problems are fairly modest, though peer problems are predictive of slightly lower engagement with the labour market overall. As expected, labour market engagement is positively associated with schooling and cognition.

6.2 Relationship with Schooling

Tables 2 and 3 showed that controlling for years of schooling modified the relationship between childhood behaviours and earnings to varying extents. We explore this further now by directly

Table 4: Determinants of Years of Schooling

	All		Males	Females	q-values
	[1]	**[2]**	**[3]**	**[4]**	**[3]-[4]**
Attention	-0.648***	-0.221***	-0.307***	-0.114**	0.023
	[0.038]	[0.045]	[0.066]	[0.054]	
Conduct	0.094***	-0.037	-0.025	-0.052	0.688
	[0.036]	[0.036]	[0.051]	[0.045]	
Emotion	0.025	0.058*	0.078	0.034	0.510
	[0.035]	[0.033]	[0.051]	[0.041]	
Peer	0.040	0.025	0.022	0.028	0.921
	[0.035]	[0.032]	[0.050]	[0.040]	
Cognition		0.726***	0.724***	0.730***	0.941
		[0.036]	[0.062]	[0.045]	
Family SES	0.856***	0.610***	0.595***	0.624***	0.675
	[0.032]	[0.032]	[0.055]	[0.044]	
Backg. Controls	X	X	X	X	
N	6952	6952	3386	3566	

Notes: Data from BCS70. Each column reports measurement-error-corrected estimates from a regression of years of schooling on standardized of socio-emotional skills, cognition, and family SES obtained from our dedicated measurement system, see equation (1). All specifications include controls for: number of siblings, dummies for first child, no dad at birth, teenage mother, and region at birth fixed effects. Specifications [1] and [2] also include a dummy for gender. Standard errors in brackets are estimated from 250 bootstrap replications: ***p < .01, **p < .05, *p < .10. FDR q-values are p-values of gender differences adjusted for multiple hypothesis testing at outcomes of interest: See notes to Table 2 for further details.

examining years of schooling as an outcome. The results are shown in Table 4, which presents estimates from the same basic regression framework as in Tables 2 and 3. In line with these earlier tables, the first column shows that, when we don't control for cognitive scores, the negative association between schooling and attention problems is extremely strong: Moving from two standard deviations below the mean of this behaviour to two standard deviations above is associated with almost 2.5 fewer schooling years.

However, as before, when controlling for cognitive scores (column 2), the associations between schooling and attention is reduced by around two thirds. Nevertheless, the high coefficient that remains does imply that much of the negative effects of attention problems operate through reduced ability to complete schooling. Moving on, the apparent effect of conduct problems switches sign and is no longer significant. On the other hand, the coefficient on emotional problems *increases* and is now significant at the 5% level.

The combined results in Table 4 and in Table 2 are worth discussing in more detail in relation to those in Papageorge et al. (2019). An important finding in that study is that some child behavioural traits are associated with outcomes of opposing signs in the labour market versus at school. The important policy implication of this finding is that schooling may not be rewarding skills appropriately and that some children who may have the skills to succeed later in life are at risk of being cast aside when they are still young. Papageorge et al. in particular find this result for their measure of 'externalizing' behaviour, which we show to be correlated to our measures of attention and conduct problems. They find that externalizing behaviours are associated with significantly positive outcomes in the labour market but significantly *negative* outcomes in terms of years of schooling. By contrast, the conduct measure from our factorization is positively associated to labour market outcomes, but we do not find a significant association with schooling. This is true after controlling for family SES and cognition as well as other skills measures, in particular attention problems, to which conduct is significantly correlated.

However, we do see this feature of opposing outcomes for a different set of behaviours: emotional problems. These behaviours are associated with negative outcomes in the labour market (Table 2), but also with significantly more years of schooling. Here, however, the policy implication is perhaps more nuanced: in terms of human capital development, it shows that the schooling system can provide a safe way to accumulate skills for those who are more anxious and less emotionally stable, and hence compensate for otherwise negative outcomes. On the other hand, in terms of the education system's role in signalling talent, our result indicates that this system may be handing credentials to people who will turn out to be less talented at work, which is clearly inefficient. The precise policy implications therefore require understanding the extent to which the returns to education depend on signalling versus human capital effects, which is still a matter of debate (see for example Ehrmantraut et al., 2020).

The third and fourth columns of Table 4 show results for this regression by gender. The association of attention problems with earnings is much larger for boys than for girls, and significantly so at the 5% level, even when we cater for multiple hypothesis testing. Relating this finding to Table 2, it is worth considering differences by gender in the extent to which schooling moderates the effects of attention. There, recall we found no significant gender difference in the association of attention with earnings, *conditional* on schooling. And, although not shown in Table 2, we see a similar pattern when *not* controlling for years of schooling. Schooling therefore does not explain the relationship of attention with earnings any more for boys than for girls. This is because, even though attention problems reduce schooling of boys much more, the relationship for boys of earnings with schooling is weaker. Equivalently, any reduction in schooling costs girls much more in terms of lost earnings.

In terms of other child behaviours, there are no significant differences by gender. Equally the associations are near identical by gender for the other confounding factors which affect schooling a great deal: cognition and family socio-economic status.

6.3 The Role of Task Sorting

We have shown that education explains some of the associations with earnings for the age-10 behavioural skills. We now examine the role of the types of jobs that individuals sort into. As discussed in Section 3, we do this by using data on task intensities from O*NET, using measures derived by Lise and Postel-Vinay (2020).

Table 5 shows regressions of three key job tasks on child behavioural skills, as well as other confounders and controls for life-cycle profiles. Before examining the role of the age 10 skills, it is worth considering the associations with schooling and cognition, shown towards the bottom. These show a clear pattern: those with more schooling and higher cognitive scores sort less into jobs which are intensive in physical tasks and more into jobs that are intensive in interpersonal and analytical tasks. The former task is therefore more indicative of 'bad' jobs, while the latter two are indicative of 'good' jobs. The bottom of Table 5 also shows a similar pattern for family socio-economic status.

The upper rows of Table 5 show results for behavioural characteristics. The top row shows that attention problems are associated with systematic sorting away from 'good' tasks/jobs and into 'bad' tasks/jobs. On the other hand aggressive behaviours seen in bad conduct are associated with sorting into good tasks, even if there is no evidence that these behavioural types are less likely to be involved with physical tasks. The evidence for emotional problems is somewhat weaker: those with lower issues sort less into physical jobs, but there is no evidence that they sort more into better interpersonally-intensive and analytical jobs. On the other hand, Table 5 clearly shows that children with peer problems eventually sort less into higher-paying analytical jobs, even if there is no strong evidence they sort differentially into physical or interpersonal tasks.

We explore gender differences in these effects in Appendix Table C.3. Broadly and interestingly, it shows that the associations of attention problems with task sorting are more evident for boys, while the associations for conduct problems are stronger for girls. Specifically, we see that girls higher in bad conduct are significantly more likely to sort into analytical tasks.[22] In line with the results on extensive-margin labour supply shown in Table C.2, this is further evidence that the positive results of bad conduct behaviours are more evident for females than for males. Finally, the table shows no noticeable differences by gender for emotional and peer problems.

Table 6 puts these pieces of evidence together by including controls for task intensities in the basic earnings regressions. For ease of comparison, the first column repeats results from Table 2. The second column shows results for the same specification, but also controlling for a) years of schooling and b) dummies for 3-digit occupations, which is the level at which job tasks are imputed. The results show that controlling for job types reduces the associations between earnings and the skills measures. Sorting into different jobs therefore mediates some of the effects of these

[22] The conservative q-value on the difference is 0.051.

Table 5: Determinants of Occupational Sorting

	Physical [1]	**Analytical** [2]	**Interpersonal** [3]
Attention	0.065***	-0.053***	-0.062***
	[0.018]	[0.016]	[0.017]
Conduct	0.001	0.044***	0.052***
	[0.013]	[0.013]	[0.015]
Emotion	-0.032***	-0.014	-0.01
	[0.012]	[0.011]	[0.012]
Peer	-0.018	-0.034***	-0.011
	[0.012]	[0.013]	[0.013]
Cognition	-0.060***	0.136***	0.091***
	[0.014]	[0.013]	[0.015]
Family SES	-0.036***	0.068***	0.062***
	[0.014]	[0.014]	[0.014]
Yrs School	-0.043***	0.105***	0.092***
	[0.005]	[0.005]	[0.005]
Backg. Controls	X	X	X
N	6952	6952	6952
Individual-years	23,451	23,451	23,451

Notes: Data from BCS70 and O*NET. Each column reports measurement-error-corrected estimates from a regression of standardized task intensities measured at the 3-digit occupation level on standardized socio-emotional skills, cognition, and family SES obtained from our dedicated measurement system, see equation (1). All specifications include controls for: number of siblings, dummies for first child, no dad at birth, teenage mother, gender, year, gender-by-year and region fixed effects. Standard errors in brackets are estimated from 250 bootstrap replications clustered at the individual level: ***p < .01, **p < .05, *p < .10.

skills. However, for conduct and emotional problems in particular, there is still a significant association that remains unexplained. Noticeably, the magnitude of the relationship of these skills with earnings is not much different from the magnitude of the relationship between earnings and cognition.

The third and fourth columns of Table 6 show gender differences in this type of mediation. As before, it shows that the gender differences that remain are most noticeable for peer problems.

6.4 Pathways Through Age-16 Behaviours and Characteristics

We have seen that age-10 behavioural skills are strongly associated with labour market outcomes, and that the various behaviours operate through differing pathways. Most strikingly, conduct problems (such as aggression) are found to be positively related to earnings, and this effect can be partially explained both by labour supply at the intensive margin and increased sorting into

Table 6: Earnings Determinants, Controlling for Occupational Sorting

	All		**Males**	**Females**	**q-values**
	[1]	**[2]**	**[3]**	**[4]**	**[3]-[4]**
Attention	-0.027***	-0.015*	-0.017*	-0.013	0.778
	[0.009]	[0.008]	[0.009]	[0.011]	
Conduct	0.037***	0.024***	0.024***	0.022***	0.866
	[0.006]	[0.005]	[0.007]	[0.008]	
Emotion	-0.029***	-0.021***	-0.018**	-0.023***	0.678
	[0.006]	[0.005]	[0.007]	[0.008]	
Peer	-0.014**	-0.007	-0.022***	0.008	0.006
	[0.007]	[0.006]	[0.008]	[0.008]	
Cognition	0.060***	0.026***	0.017**	0.032***	0.245
	[0.007]	[0.006]	[0.008]	[0.009]	
Family SES	0.046***	0.030***	0.048***	0.008	0.001
	[0.007]	[0.006]	[0.008]	[0.008]	
Yrs School	0.049***	0.027***	0.016***	0.041***	0.000
	[0.003]	[0.003]	[0.003]	[0.005]	
Occupation dummies		X	X	X	
Backg. Controls	X	X	X	X	
N	6952	6952	3386	3566	
Individual-years	23,451	23,451	11,404	12,047	

Notes: Data from BCS70. Each column reports measurement-error-corrected estimates from a regression of log real monthly earnings as the dependent variable. See notes to Table 2. Specifications [2] to [4] add UK-SOC2010 (3-digits) occupational dummies as controls. Standard errors in brackets are estimated from 250 bootstrap replications clustered at the individual level: ***p < .01, **p < .05, *p < .10. FDR q-values are p-values of gender differences adjusted for multiple hypothesis testing at outcomes of interest.

good jobs. Attention problems have strong negative effects, in large part because they affect the ability to find good jobs as well as schooling outcomes. Emotionally problematic behaviours, such as apparent anxiety, lead to reduced labour supply. However, these otherwise negative outcomes are compensated by increased schooling. At the same time problems with peers are also later associated with lower wage rates, but their effect on labour supply differs by gender.

Overall, therefore, it is clear that a) age-10 behaviours affect labour market outcomes through very different channels, b) a sizeable proportion of the effects on earnings remain unexplained by the channels we have investigated so far. To explore these aspects further, we explore behaviours and other characteristics measured between childhood and adult labour market engagement using the BCS70 sweep at age 16. We focus on three different domains that are *a priori* likely to be important and about which we have useful data: social engagement, such as breadth of friendship networks; attitudes to work; and well-being and emotional health. As discussed in section 3, the response rate to the survey was lower at age 16 so here we necessarily work with smaller samples.

Additionally, because the samples for these age-16 characteristics do not coincide perfectly, we examine each feature separately rather than all jointly.[23]

We first assess relationships between the age-10 behaviours and the age-16 characteristics of interest. Table 7 shows these in compact format, pooled across gender, with regressions split by gender shown in Appendix Table C.4.

The first column of Table 7 shows a regression of teenage social attainment on earlier socio-emotional behaviours as well as the standard additional controls. As expected, teen socialization is strongly negatively affected by earlier peer problems. On the other hand, it is associated positively with conduct behaviours. This relationship therefore shows some of the positive skills that those with more aggressive natures, and which likely pay-off later in work, are able to accumulate. It is also noteworthy that teen social attainment is related negatively to emotional problems and to cognition. This latter association in particular shows the trade-off between time spent socializing and in education.

The second column of Table 7 looks at determinants of occupational interests. As discussed briefly in section 3, the occupational interests data capture attitudes across six areas of work: business; practical; living; commerce; caring, and art. We focus here on interests in business, which the literature has found to be important (see e.g. Wiswall & Zafar, 2015) and which we expect to be most related to later earnings. Table 7 shows that relative interests in business are not affected by cognitive ability nor by background family socio-economic status, but are strongly negatively affected by problems of attention. This result indicates that the negative effects on schooling of inattention, and the problem behaviours associated with low conscientiousness, are widespread. Not only do these behaviours negatively affect grades directly (Richardson et al., 2012), they also seem to affect relevant career aspirations which are nurtured at school. Looking at the results by gender shown in Appendix Table C.4, the relevant point estimate is larger in absolute size for boys than girls, although the low sample size makes inference on these differences problematic. For completeness, we show parallel regressions for attitudes to the other areas of work in Appendix Table C.5.

The final column of Table 7 examines mental health at age 16, as captured by a reverse coding of the malaise score. Here the salient determining factor at age 10 is, not surprisingly, that related to emotional problems. Conditional on the other background factors, moving from two standard deviations below the mean to two standard deviations above on this scale raises the score of age-16 mental health problems by 0.30 standard deviations. Again Appendix Table C.4 shows the same regression by gender, and again it shows that the effect seems stronger for boys than girls. Here, however, the difference across genders is strongly significant, providing strong evidence on gender differences in the generation of mental health in adolescence.

[23] Although not shown here, when we do form samples including more than one of the age-16 characteristics, results are little changed. Results available upon request.

Table 7: Determinants of Teen Characteristics

	Teen Socialization [1]	**Attitudes Business [2]**	**Mental Health [3]**
Attention	0.025	-0.147***	0.012
	[0.035]	[0.042]	[0.039]
Conduct	0.060**	0.014	-0.039
	[0.027]	[0.034]	[0.029]
Emotion	-0.057**	0.021	-0.071***
	[0.026]	[0.028]	[0.025]
Peer	-0.128***	0.051	-0.044*
	[0.026]	[0.031]	[0.024]
Cognition	-0.079***	0.011	0.018
	[0.031]	[0.035]	[0.030]
Family SES	-0.035	-0.011	0.038
	[0.026]	[0.032]	[0.024]
Backg. Controls	X	X	X
N	3751	2057	3182

Notes: Data from BCS70. Each column reports measurement-error-corrected estimates from regressions of standardized age-16 variables on standardized socio-emotional skills, cognition, and family SES. Teen socialization is a predicted score obtained from our dedicated measurement system, see equation (1). Attitudes for Business is the deviation of the interest for business with respect to mean occupational interest. Mental health is the total Malaise score reverse-coded. All specifications include controls for: number of siblings, dummies for first child, no dad at birth, teenage mother, gender, and region at birth fixed effects. Standard errors in brackets are estimated from 250 bootstrap replications: ***p < .01, **p < .05, *p < .10.

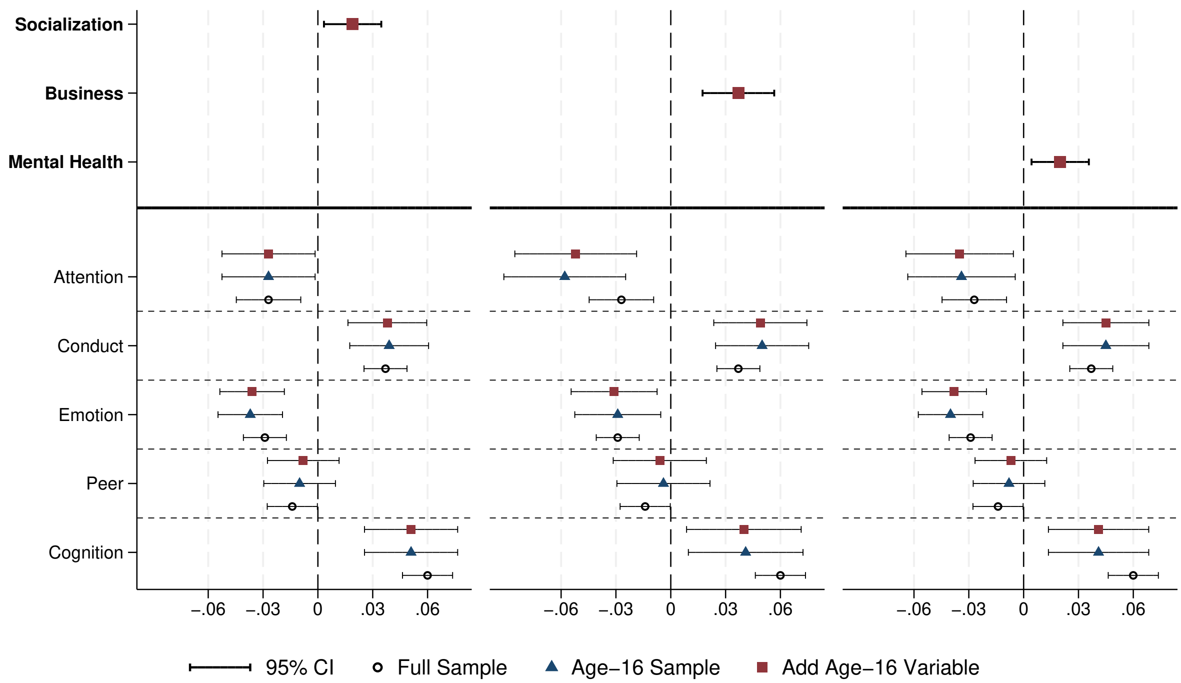
We turn now to examining how these age-16 measures relate to later outcomes in the labour market, and how controlling for them modifies the relationship between the adult outcomes and the childhood skills. To this end, Figure 1 shows results from earnings regressions with the same covariates as reported in Table 2, but now including the age-16 measures in addition. Across the three plots, the hollow circles reproduce results from Table 2 for ease of comparison. In the left-hand plot the blue triangles show results for the same specification but using a restricted sample for which we have information on our first age-16 characteristic of interest: teen socialization. A comparison of these markers shows that results across these samples are very similar. Results including the social attainment variable are then displayed with the red squares. The top-most square shows that socialization has an effect on adult earnings that is small but significantly positive. The lower panels show a feature of the results that are present with all the age-16 characteristics: the estimated relationships of the age-10 skills with earnings are little changed when including the extra control. This result can be interpreted in two ways: first it shows that the age-16 characteristics quantitatively explain at most a small part of the relationship between earlier-measured skills and later outcomes. Second, and equally, it shows that the effect of the age-10 measures skills remains strong despite the inclusion of additional relevant factors.

The middle plot repeats this exercise but for career interests in business. The top-most estimate shows that those with a stronger relative preference for business occupations do earn more later in life. The lower panels of Figure 1 again show that business interests explain little of the effects of the age-10 behaviours, though the estimated coefficient on attention problems is reduced by around 10%, showing that attitudes to work do mediate the effects of this behaviour partially. In Appendix Table C.5, we show equivalent results for the other six areas of work interests. We find a strong positive effect of practical interests, such as those related to science, and a negative effect of interests in the arts.

The right-most plot shows results for age-16 mental health. Again, as expected, improvements in mental health are associated with higher earnings later on. Here, moving from the two standard deviations below the mean on the score of mental health, to two standard deviations above the mean is estimated to be associated with over 8% higher earnings, conditional on the full vector of controls, including years of schooling. Again, looking at the lower panels, it seems that controlling for age-16 mental health does not alter the effect of age-10 behaviour noticeably.

Our overall conclusion from Table 7 and Figure 1 is that various age-16 characteristics signal important pathways from age-10 behaviours to adult outcomes, and that these pathways work in expected ways. However, it seems that, at least with the measures we have available, their role in mediating the effect of age 10 behaviours is small.

Figure 1: Earnings Determinants, Including Teen Characteristics



Notes: Data from BCS70. The figure compares estimates and confidence intervals at a confidence level of 95% from a regression of log real monthly earnings on standardized socio-emotional traits, cognition, and family socio-economic status for the main sample (6952 observations) and age-16 sample (3377 observations). We use the age-16 sample to provide estimates of log monthly earnings on age-16 variables: teen socialization (left figure, attitudes to business (middle figure) and mental health (right figure). All specifications control for: gender, gender-by-year, number of siblings, dummies for first child, no dad at birth, teenage mother, year and region fixed effects. Standard errors in brackets are estimated from 250 bootstrap replications clustered at the individual level: ***p < .01, **p < .05, *p < .10.

6.5 Other Long-Run Outcomes: Health and Health Behaviours

This paper focuses on the relationship of child skills with labour market outcomes. Nevertheless it is informative to look at other adult outcomes additionally. Aside from the importance of understanding these outcomes in themselves, we do this primarily to test the predictive validity of the skills constructs. Here we focus on well-being and mental health, as well as behaviours related to health and risk-taking. We compare estimated associations broadly to those found in Goodman et al. (2015), who discuss relationships with various types of socio-emotional skills measured using a range of constructs.

The estimated relationships using our data are shown in Table C.6. The first two columns show associations with two measures of alcohol intake: one is the score on the WHO's Alcohol Use Disorders Identification Test (AUDIT), and the other a simpler measure of frequency of drinking. Goodman et al. find rich patterns for this outcome which reflect the combined effects of the multi-faceted use of alcohol, including its role in social behaviour as well as in stress relief. Specifically they broadly find a strong positive relationship with characteristics which align with our measure of conduct problems, and a strong *negative* relationship with peer problems, likely reflecting lower social engagement. They also find some positive association with similar characteristics to our measure of attention problems, and little clear relationship with problems of emotion. Combined across the first two outcomes, these patterns are highly consistent with those found for our skills measures. The third column then shows frequency of smoking, which again reflects a variety of socio-emotional needs. In line with results in Goodman et al. we find a strong negative association with emotional problems but strong positive associations with problems of attention and conduct.

The next five columns show various measures of well-being and mental health. Of these, Goodman et al. focus most on life satisfaction, shown in our sixth column. Again, exactly in line with their discussion we find strong negative associations with attention and peer problems. The other related outcomes show somewhat similar patterns, although there are interesting differences which are worth drawing out. As would be expected, for metrics more explicitly related to mental health, such as the malaise score and the GHQ-12, there is a larger role for emotional problems. Interestingly, for job satisfaction, the effect of conduct problems stands apart: Worse conduct in childhood is associated with *higher* satisfaction in work. This result is clearly consistent with our results on the labour market discussed previously.

The final column of Table C.6 shows associations with number of arrests, which Prevoo and ter Weel (2015) find to be positively associated with low conscientiousness. We find similar results for our attention problems construct. Going beyond the focus of Prevoo and Ter Wiel's analysis, we find interesting results for the other socio-emotional skills. Those with more childhood emotional problems such as anxiety and timidity are much less likely to be arrested, while those with higher conduct problems related to aggression are, unsurprisingly *more* likely to be arrested.

Overall, therefore, we find rich patterns of our measured skills with outcomes beyond the labour market that allign with relationships we see from outside evidence.

6.6 Additional Analyses and Robustness

We finish this section by briefly describing a range of additional analyses to show the robustness of our key results.

Factorization by Gender: Throughout the analysis we have explored gender as an important interacting characteristic. A natural and important question is whether any gender differences we find are because of differences in the transmission of skills to later outcomes or differences in the skills constructs themselves. To investigate this we repeat some of the analysis for the gender-specific samples but using the *pooled* factorization. Table C.7 shows results for our main outcomes: Earnings, Schooling and Social Behaviour. It shows that results with the pooled factorization are little changed from those using the gender-specific factorization that we showed earlier. This implies that any gender differences we see are indeed due to differences in the transmission of skills.

Selection into the Sample: One concern is that individuals differentially drop out of the survey depending on their socio-emotional skills. It seems intuitively plausible that those with behavioural problems are less likely to live stable adult lives and respond to surveys. We investigate this simply within our analysis by examining a binary indicator equalling one if the individual appears in *all* waves, though not necessarily in the labour market. Recall that to be in our sample, the individual has to appear in the labour market in at least one wave through adulthood. Results from a linear probability model are shown in Table C.8. Among the skills of interest, it shows that those with emotional problems, and females in particular, are more likely to appear in all waves conditional in appearing in one, but both males and females with conduct problems are less likely to appear.

Table C.9 then shows what impact this differential survey participation has on estimated effects. It shows our main results alongside those obtained by reweighting individuals depending on the inverse of their probability of appearing in all waves. Such an approach down-weights those with higher emotional problems and up-weights those with conduct problems. The table shows that for the age-10 skills, such a reweighting has little impact. Only for the effect on schooling of cognition, which also has a large effect on survey participation, does reweighting change estimates noticeably.

Mindset: In Section 5 we discussed that mindset skills captured by questions from the LAWSEQ self-esteem scale appeared as a separate factor when included in the EFA. We also discussed that this factor suffered from poor internal consistency, and so was dropped from our preferred specification. We now show results when including self-esteem for our main outcomes, in Table C.10. Self-esteem itself has a small positive effect on wages and a negative off-setting effect on hours at the intensive margin. For earnings overall and for schooling, self-esteem is less relevant than any of the main skills we examine. The table also shows that estimates for the other skills are little affected when self-esteem is included.

Non-linearities: Our analysis throughout has been based on a model which is both linear in parameters and in skills measures themselves. The size of our dataset precludes a detailed analysis of non-linearities. Nevertheless we provide some evidence on this front in Figure C.1, which shows group means of our outcome variables by terciles of the (noisy) factor scores. These group means are obtained after stripping out the effects of the basic confounders. With a few possible exceptions, it shows broadly that there is very little evidence of any non-linearities across any of the outcomes.

Parental Behaviours: Finally, we investigate the extent to which the estimated effects of our skills are confounded by parenting style. Although we control for family socio-economic status throughout the analysis, it is possible that the effects we see are driven by either a) a correlation of behavioural issues with inadequate parenting, b) a causal feedback from child nature to parental stress and a deterioration of parenting itself. To investigate this we estimate a factor which we label 'parental warmth' from additional questions asked of parents in the age-5 wave.[24] Results including this measure are shown in Table C.11, which shows that parental warmth neither has any apparent effect on long-run outcomes when controlling for skills and family socio-economic background, nor it alters the estimates for the age-10 skills.

7 Summary and Conclusions

In this paper we investigate the relationship between early measures of socio-emotional skills and later economic outcomes using data from the 1970 British Cohort Study. Using a measurement model which takes into account different aspects of childhood development as observed by teachers in school, we identify a four-factor representation of child socio-emotional skills and explore their association with various adult outcomes. Our findings reveal that attention, peer and emotional problems are *negatively* related to earnings, while - contrary to conventional hypotheses - conduct problems are predictive of *positive* labour market outcomes. The analysis also explores the role of career preferences, socialization, and mental health, but finds that none of them fully explains the observed relationships.

The findings add to the existing literature on the economic returns to socio-emotional skills in three distinct ways. First, we present a new and methodologically robust analysis of childhood

[24] We use 24 items from the Maternal Self-completion Questionnaire which are reversed in scale to capture non-authoritarian child-rearing and world views. We run an EFA on these items and after several iterations, we retain nine items which are used to construct parental warmth. These are: 'nothing worse than not respect parents', 'children accept what parents say', 'children with own ideas will not learn', 'children should not talk back to parents', 'a good child is one not told twice', 'children not talk at table', 'equality but husband has main say', 'not let others stand in way and parents sort out children quarrels'

socio-emotional skill, arriving at a four-factor representation that closely maps into the domains of the Strength and Difficulties Questionnaire (SDQ). This gives our results an immediate interpretative framework and, since the SDQ has only been recently adopted in many longitudinal studies, this study could be considered the first to illustrate the relationship between the SDQ and later economic outcomes. Second, we demonstrate that the relationship between skills and outcomes is quite complex. This challenges a simplistic interpretation of skills or problem behaviours in childhood, underscoring the need for more research on the measurement of skills as well as targeted educational interventions. Third, we explore a number of potential pathways, each demonstrating significant associations with childhood skills, but show that none of these can fully account for the observed associations, suggesting the presence of additional mechanisms that are still unexplored.

Several important policy relevant implications emerge from this analysis. Specifically, the result that child socio-emotional skills are predictive of a number of adult economic outcomes, even conditional on a range of confounders and mediators, provides strong support for policies and interventions that focus on the development of these skills in the early years. This clearly calls for integrating socio-emotional learning into the school curricula. Although this need is already recognised in the UK educational context, no uniform approach has emerged as yet (see Clarke et al., 2015 and Donnelly et al., 2020 for recent reviews of UK initiatives). Another consideration is that the positive association between conduct problems and labour market outcomes suggests a need to reconsider discipline policies in schools. It is possible that what is often identified as aggressive behaviour is the *adaptive* response to a competitive environment (e.g. a classroom or a work establishment). Rather than a punitive approach, there could be more focus on understanding the causes of the disruptive behaviour and teachers could be trained to identify strategies which help children to channel these tendencies in more productive ways. This approach would obviously require additional resources, and would need to take into account the fact that conduct problems or aggressive behaviour might have negative impacts on other children's learning and mental health.

There are several limitations of our analysis that are worth mentioning. Perhaps most importantly, the study relies on data on childhood skills collected in the early 1980s, when the children were 10 years old. The specific features of the system of education and the expectations about children's behaviour prevalent in the UK at the time might therefore have influenced the assessments provided by teachers and indeed even the specific wording of the questionnaire. This factor could affect the applicability of the results to more recent settings. Moreover, as we discuss above, the data suffer from attrition and, while we conduct some checks to assess the effect on our results, this is an issue we cannot fully address. Lastly, like many other studies in this literature, our analysis is observational, and so does not establish causality. Although we are careful in considering the effects of a range of demographic and contextual factors, there might be other aspects, such as peer influences, school characteristics, or family dynamics that confound or mediate the observed associations.

References

Acemoglu, D., & Restrepo, P. (2018): The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, *108*(6), 1488–1542.

Acemoglu, D., & Restrepo, P. (2019): Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, *33*(2), 3–30.

Alan, S., Baysan, C., Gumren, M., & Kubilay, E. (2021): Building social cohesion in ethnically mixed schools: An intervention on perspective taking. *The Quarterly Journal of Economics*, *136*(4), 2147–2194.

Alan, S., Boneva, T., & Ertac, S. (2019): Ever failed, try again, succeed better: Results from a randomized educational intervention on grit. *The Quarterly Journal of Economics*, *134*(3), 1121–1162.

Almlund, M., Duckworth, A. L., Heckman, J., & Kautz, T. (2011): Personality psychology and economics. In *Handbook of the Economics of Education* (pp. 1–181). Elsevier.

Anderson, M. L. (2008): Multiple inference and gender differences in the effects of early intervention: A reevaluation of the abecedarian, perry preschool, and early training projects. *Journal of the American Statistical Association*, *103*(484), 1481–1495.

Attanasio, O., Blundell, R. W., Conti, G., & Mason, G. (2018): *Inequality in socioemotional skills: A cross-cohort comparison*, IFS Working Papers, WP20/11.

Attanasio, O., De Paula, Á., & Toppeta, A. (2020): *The persistence of socio-emotional skills: Life cycle and intergenerational evidence*, National Bureau of Economic Research, 27823.

Autor, D. (2022): *The labor market impacts of technological change: From unbridled enthusiasm to qualified optimism to vast uncertainty*, National Bureau of Economic Research, 30074.

Benjamini, Y., Krieger, A. M., & Yekutieli, D. (2006): Adaptive linear step-up procedures that control the false discovery rate. *Biometrika*, *93*(3), 491–507.

Bolt, U., French, E., Maccuish, J. H., & O'Dea, C. (2021): *The intergenerational elasticity of earnings: Exploring the mechanisms*, CEPR Discussion Paper No. DP15975.

Borghans, L., Duckworth, A. L., Heckman, J. J., & Ter Weel, B. (2008): The economics and psychology of personality traits. *Journal of Human Resources*, *43*(4), 972–1059.

Borghans, L., Ter Weel, B., & Weinberg, B. A. (2014): People skills and the labor-market outcomes of underrepresented groups. *ILR Review*, *67*(2), 287–334.

Brodman, K., Erdmann, A. J., Lorge, I., Wolff, H. G., & Broadbent, T. H. (1951): The cornell medical index-health questionnaire: Ii. as a diagnostic instrument. *Journal of the American Medical Association*, *145*(3), 152–157.

Buss, D. M., & Shackelford, T. K. (1997): Human aggression in evolutionary psychological perspective. *Clinical Psychology Review*, *17*(6), 605–619.

Butler, N., Desoitidou, S., & Shepherd, P. (1980): *British cohort study (bcs70) ten-year follow-up: A guide to the bcs70 10-year data)* (tech. rep.). Social Statistics Research Unit, City University.

Campbell, D. T., & Fiske, D. W. (1959): Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychological Bulletin*, *56*(2), 81–105.

Caye, A., Rocha, T. B.-M., Anselmi, L., Murray, J., Menezes, A. M., Barros, F. C., Gonçalves, H., Wehrmeister, F., Jensen, C. M., Steinhausen, H.-C., et al. (2016): Attention-deficit/hyperactivity disorder trajectories from childhood to young adulthood: Evidence from a birth cohort supporting a late-onset syndrome. *JAMA Psychiatry*, *73*(7), 705–712.

Clarke, A. M., Morreale, S., Field, C.-A., Hussein, Y., & Barry, M. M. (2015): *What works in enhancing social and emotional skills development during childhood and adolescence. a review of the evidence* *on the effectiveness of school-based and out-of-school programmes in the uk.* (tech. rep.). The World Health Organization Collaborating Centre for Health Promotion Research, National University of Ireland Galway.

Closs, S. (1978): An algorithm for integrating preference and like–dislike responses to the same test items. *Journal of Occupational Psychology*, *51*(2), 147–154.

Conners, C. K. (1969): A teacher rating scale for use in drug studies with children. *Americal Journal of Psychiatry*, (126), 884–888.

Conti, G., Frühwirth-Schnatter, S., Heckman, J. J., & Piatek, R. (2014): Bayesian exploratory factor analysis. *Journal of Econometrics*, *183*(1), 31–57.

Cunha, F., Heckman, J. J., & Schenach, S. M. (2010): Estimating the technology of cognitive and noncognitive skill formation. *Econometrica*, *78*(3), 883–931.

Del Bono, E., Kinsler, J., & Pavan, R. (2020): *Skill formation and the trouble with child non-cognitive skill measures*, IZA Discussion Paper No. 13713.

Deming, D. J. (2017): The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, *132*(4), 1593–1640.

Dickerson, A., & Morris, D. (2019): The changing demand for skills in the uk. *Centre for Vocational Education Research, Research Paper*, *20*.

Donnelly, M., Brown, C., Batlle, I. C., & Sandoval-Hernández, A. (2020): *Developing social and emotional skills: Education policy and practice in the uk home nations* (tech. rep.). Nesta Reports.

Edin, P.-A., Fredriksson, P., Nybom, M., & Öckert, B. (2022): The rising return to noncognitive skill. *American Economic Journal: Applied Economics*, *14*(2), 78–100.

Ehrmantraut, L., Pinger, P., & Stans, R. (2020): *The expected (signaling) value of higher education*, CESifo Working Paper, 8589.

Feng, S., Han, Y., Heckman, J. J., & Kautz, T. (2022): Comparing the reliability and predictive power of child, teacher, and guardian reports of noncognitive skills. *Proceedings of the National Academy of Sciences*, *119*(6), e2113992119.

Fraguas, D., Díaz-Caneja, C. M., Ayora, M., Durán-Cutilla, M., Abregú-Crespo, R., Ezquiaga-Bravo, I., Martín-Babarro, J., & Arango, C. (2021): Assessment of school anti-bullying interventions: A meta-analysis of randomized clinical trials. *JAMA Pediatrics*, *175*(1), 44–55.

Gammage, P. (1975): *Socialisation, schooling and locus of control* (Doctoral dissertation). Bristol University.

Goodman, A., Joshi, H., Nasim, B., & Tyler, C. (2015): Social and emotional skills in childhood and their long-term effects on adult life. *London: Institute of Education*.

Goodman, Lamping, D. L., & Ploubidis, G. B. (2010): When to use broader internalising and externalising subscales instead of the hypothesised five subscales on the strengths and difficulties questionnaire (sdq): Data from british parents, teachers and children. *Journal of Abnormal Child Psychology*, *38*, 1179–1191.

Goodman, R. (1997): The strengths and difficulties questionnaire: A research note. *Journal of Child Psychology and Psychiatry*, *38*(5), 581–586.

Heckman, J. (2008): Schools, skills, and synapses. *Economic Inquiry*, *46*(3), 289–324.

Heckman, J., Pinto, R., & Savelyev, P. (2013): Understanding the mechanisms through which an influential early childhood program boosted adult outcomes. *American Economic Review*, *103*(6), 2052–86.

Heckman, J., Stixrud, J., & Urzua, S. (2006): The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, *24*(3), 411–482.

Horn, J. (1965): A rationale and test for the number of factors in factor analysis. *Psychometrika*, *30*(2), 179–185.

Jin, W. (2022): *Occupational polarisation and endogenous task-biased technical change* (tech. rep.). University College London.

Johnston, D., Propper, C., Pudney, S., & Shields, M. (2014): Child mental health and educational attainment: Multiple observers and the measurement error problem. *Journal of Applied Econometrics*, *29*, 880–900.

Joreskog, K. (1971): Statistical analysis of sets of congeneric tests. *Psychometrika*, *36*, 109–133.

Kautz, T., Heckman, J. J., Diris, R., Ter Weel, B., & Borghans, L. (2014): *Fostering and measuring skills: Improving cognitive and non-cognitive skills to promote lifetime success*, National Bureau of Economic Research, 20749.

Lawrence, D. (1981): The development of a self-esteem questionnaire. *British Journal of Educational Psychology*, *51*(2), 245–251.

Levine, R., & Rubinstein, Y. (2017): Smart and illicit: Who becomes an entrepreneur and do they earn more? *The Quarterly Journal of Economics*, *132*(2), 963–1018.

Lim, S., & Jahng, S. (2019): Determining the number of factors using parallel analysis and its recent variants. *Psychological Methods*, *24*(4), 452–467.

Lindenlaub, I. (2017): Sorting multidimensional types: Theory and application. *The Review of Economic Studies*, *84*(2), 718–789.

Lise, J., & Postel-Vinay, F. (2020): Multidimensional skills, sorting, and human capital accumulation. *American Economic Review*, *110*(8), 2328–2376.

Niclasen, J., Teasdale, T. W., Andersen, A.-M. N., Skovgaard, A. M., Elberling, H., & Obel, C. (2012): Psychometric properties of the danish strength and difficulties questionnaire: The SDQ assessed for more than 70,000 raters in four different cohorts. *PloS One*, *7*(2), e32025.

Nunnally, J. C., & Bernstein, I. H. (1994): *Psychometric Theory*. McGraw Hill.

Papageorge, N. W., Ronda, V., & Zheng, Y. (2019): *The economic value of breaking bad: Misbehavior, schooling and the labor market*, National Bureau of Economic Research, 25602.

Prevoo, T., & ter Weel, B. (2015): The importance of early conscientiousness for socio-economic outcomes: Evidence from the british cohort study. *Oxford Economic Papers*, *67*(4), 918–948.

Richardson, M., Abraham, C., & Bond, R. (2012): Psychological correlates of university students' academic performance: A systematic review and meta-analysis. *Psychological Bulletin*, *138*(2), 353.

Rutter, M. (1967): A children's behaviour questionnaire for completion by teachers: Preliminary findings. *Child Psychology & Psychiatry & Allied Disciplines*.

Sorrenti, G., Zölitz, U., Ribeaud, D., & Eisner, M. (2020): The causal impact of socio-emotional skills training on educational success. *University of Zurich, Department of Economics, Working Paper*, (343).

Volk, A. A., Dane, A. V., & Al-Jbouri, E. (2022): Is adolescent bullying an evolutionary adaptation? a 10-year review. *Educational Psychology Review*, *34*(4), 2351–2378.

Wehner, C., Schils, T., & Borghans, L. (2016): Personality and mental health: The role and substitution effect of emotional stability and conscientiousness. *Available at SSRN 2864838*.

Weinberger, C. J. (2014): The increasing complementarity between cognitive and social skills. *Review of Economics and Statistics*, *96*(4), 849–861.

Wiswall, M., & Zafar, B. (2015): Determinants of college major choice: Identification using an information experiment. *The Review of Economic Studies*, *82*(2), 791–824.

Appendix for:

The Economic Value of Childhood Socio-Emotional Skills

Emilia Del Bono, Ben Etheridge & Paul Garcia

A Further Details on the Data and Methodology

A.1 Variable Construction

For the child development items presented in Table 1, we use the harmonized teacher reports. These are produced by Closer[25] and designed to be compatible with similar items from other surveys, such as the National Child Development Survey. The derived scores are given on a scale of 0-2. These scores address the issue of heaped points in the original distribution, and result in a distribution suitable for polychoric analysis.

Our years of schooling variable is defined as total completed years in school by age 26. Accordingly the vast majority of measures are taken from the age-26 sweep. For those not appearing in this sweep we take the first subsequent report in following sweeps. In practice, years of schooling is calculated from the highest qualification attained. For example, individuals leaving school at age 16 and before completing O-levels are assigned 10 years, while those completing O-levels are assigned 11 years. Holders of bachelors degrees are computed to have 16 years. In cases where respondents do not report a qualification level, we use the reported age of leaving education instead, where available.

Our earnings variable is usual take-home pay excluding bonuses for employees. Survey respondents report the relevant time period for which their earnings are received, which we use to convert to a monthly frequency. To address extreme values, we windsorize the top and bottom 3% of values within gender and sweeps.

For hours, we use usual hours worked per week (excluding meal breaks). Similarly to earnings we windsorize the top and bottom 3% within gender and sweeps. Self-employed individuals, who typically do not report hours, are excluded from the sample. Wages for employees are computed as the ratio of earnings to hours.

Family socio-economic status is derived from a factorization of four variables. The first variable is family income, categorized into eight bands. The second variable captures parent qualifications. For this we first use the father's qualification level. If father's qualifications are not reported, we use the qualification level of the mother. The third variable is socio-economic status, specifically the broad occupation group of the father or, if the father is unemployed, the occupation of the mother. Lastly, we include a binary variable indicating whether either parent holds a managerial position. In cases where one of these variables is missing (e.g., occupational status when both parents are unemployed), we impute values as discussed below. All of these variables are reported in the age-10 sweep.

Other control variables are obtained directly from the dataset. These include categorical variables indicating the presence of the father in the household at the time of birth, whether the mother

[25] https://discovery.closer.ac.uk/

was a teenager at the time of birth, and the region of birth, all collected in the original age-0 sweep. Additionally, we consider the number of siblings and birth order as reported in the age-10 sweep.

As discussed in Section 6 we use importance scores from 218 descriptors from O*NET. These are from items from the sections on Skills (35 items, 'complex problem solving' to 'technical skills'), Abilities (52 items, 'cognitive' to 'sensory'), Knowledge (33 items, 'arts and humanities' to 'mathematics and science'), Work Context (57 items, 'interpersonal relationships' to 'structural job characteristics') and Work Activities (41 items, 'information input' to 'work output').

We also incorporate items related to social behavior at age 16, as documented in Table B.6. For assessing mental health, we consider the total malaise score reported in the survey at age 16, which encompasses 22 items covering aspects such as quality of sleep, feelings of misery, and occurrence of headaches or backaches. This score ranges from 0 to 44 and is standardized for our analysis.

A.2 Data on Occupational Interests

As discussed in Section 3 we use data on occupational interests from the BCS survey collected in the age 16 sweep, in 1986. These data were archived un-processed for many years and only released in 2016. They come from a computer-assisted survey in which respondents were presented with a list of 30 pairwise options for jobs they would like to perform. These options were arranged in six menus which were designed to depend on the respondent's hypothetical skill level in the labour market, and which the respondent was allowed to select depending on their anticipated final schooling level. For example the first menu asks respondents to choose between 'Repair holes in roads' and 'Lift potatoes from fields', while the sixth menu asks respondents to choose between 'Do research on new ways of producing energy' and 'Study the causes of diseases'. In their chosen menu, respondents were forced to choose a preferred outcome, but also asked to rate each outcome with an intensity of their interest. As discussed in Section 3, the raw data were then processed according to the Closs algorithm (Closs, 1978), which provides individual-level scores on the overall interest in each of six career tracks: business occupations; practical; living; communication; art and caring occupations.

In our analysis we use these processed scores. As presented in Tables 7, C.4 and C.5 we use the interest score for the relevant career track as the outcome variable. To control for overall enthusiasm for work we control for the total score across all career tracks, which varies noticeably across individuals and skill level. Accordingly we interpret our results as capturing relative interests. In this way we show that certain types have more or less interest in more challenging and higher-paying career tracks relative to less challenging and lower paying ones.

Table A.1: Summary Statistics of Main Variables

Variables	N	Mean	SD	Min	Max
Year	23451	2004	1	1996	2016
Time-Varying					
Log Monthly Earnings	23451	7.17	0.61	5.18	8.55
Log Hourly Wages	23451	2.16	0.48	-0.29	4.52
Log Monthly Hours	23451	5.02	0.35	3.95	5.58
London	23451	0.08	0.27	0	1
Fixed					
Years of Schooling	6952	12.26	2.31	0	17
Female	6952	0.51	0.50	0	1
Number siblings	6952	1.58	1.04	0	8
First child	6952	0.42	0.49	0	1
Dad not present (age 0)	6952	0.04	0.19	0	1
Teenage mother (age 0)	6952	0.08	0.28	0	1
Standardized variables					
Tasks Intensities					
Analytical	23451	0	1	-2.14	2.20
Interpersonal	23451	0	1	-2.24	2.11
Physical	23451	0	1	-1.54	2.47
Age-10 Skills					
Attention	6952	0	1	-1.47	3.10
Conduct	6952	0	1	-1.07	4.86
Emotion	6952	0	1	-1.60	2.85
Peer	6952	0	1	-1.82	3.28
Cognition	6952	0	1	-3.99	2.69
Family SES	6952	0	1	-2.02	2.64
Age-16 Skills					
Business Orientation	1847	0	1	-2.89	2.89
Teen Socialization	3377	0	1	-2.33	2.12
Mental Health	2876	0	1	-1.73	5.95

Notes: Data from BCS70 and O*NET. The table shows summary statistics for key variables of this study. Labor market information on earnings, wages, and hours, is estimated using information on 6 waves from 1996 to 2016 for the main sample (6952 individuals with complete information at age 10). Estimates for occupational task intensities are obtained by using UK-SOC2010, ISCO-08, and O*NET and crosswalk tables. Years of Schooling are estimated by using information on the highest academic qualification achieved and the age at which an individual leaves full-time education as reported in wave 1996. Missing years of schooling for non-participants in 1996 are completed using information from subsequent waves. Factor scores for skills, occupational orientation, mental health, and socio-demographic characteristics, are obtained from waves 1970, 1980 and 1986. See Section 4 for detailed information on the construction of skills.

Table A.2: Sample Statistics: Age-10 and -16 Variables

Age 10	**N observations**	**Age 16**	**N observations**
Number of obs.	14870	Number of obs.	11815
Cognition		**Teen Socialization**	
(BAS, Maths, Reading Tests, 8 items)		(Friends & Outside, Att. Scales, 12 items)	
Complete	11108	Complete	4318
Imputed	1755	Imputed	2272
Total	12863	Total	6590
Child Development		Complete info. Age-10 + Age-16 social + labour market attachment	**3377**
(Rutter, Conners, 42 items)			
Complete	9686		
Imputed	3016		
Total	12702		
Family SES		**Occupational Interests**	
(family income, parental qual., 4 items)		(JIIG-CAL Quest.)	
Complete	11860	Complete	3475
Imputed	1835		
Total	13695		
Complete info. Age-10 + labour market attachment	**6952**	Complete info. Age-10 + Age-16 social + occ. Interests + labour market attachment	**1847**

Notes: Data from BCS70. The table outlines the count of completed and imputed cases for all age-10 and age-16 variables used in this study. The main sample consists of individuals with full information after imputation on age-10 measures and labor market attachment. The sample is significantly smaller when including age-16 variables due to high attrition levels in wave 1986. The sample decreases further when accounting for respondents who completed the JIIG-CAL Questionnaire (Job Ideas and Information Generator - Computer-Assisted Learning). Sample sizes are detailed in each table throughout the paper.

A.3 Imputation

Our statistical analysis faces the challenges of high attrition and non-response in the BCS70, which vary significantly across sweeps. We deal with missing items by using a random forest imputation algorithm under the assumption of missing at random (MAR).[26] Acknowledging that this is a strong assumption, we impute missing observations only for those individuals with one missing item at most within each scale. Analogously, we impute missing test scores only for those with one missing cognitive test score out of the eight available.

Table A.3 shows the number of tests and scales we use in our factor analysis and evidences the number of individuals with complete cases, missing values and imputations performed for each scale/test. Although 14,780 individuals were interviewed in the age-10 survey, we have information from teachers' responses to the Child Behaviour Scale for only 65% of them. This response rate is higher for other scales such as Lawrence Self-Esteem and CARALOC, which are self-reported by the child, and stands at approximately 80% of the achieved sample. Column 4 summarizes the number of individuals with missing observations, that is, the number of individuals with 1 or more missing items (excluding those who did not answer any question) within each scale. We perform random forest imputations using information from individuals that answered all but one question within each scale. As shown in column 5, around 80% of the individuals with missing observations satisfy this criterion and thus a full set of measures is obtained and used in the analysis. The problem of missing items is generally much lower for cognitive test scores, affecting only around 21% of the achieved sample.

At age 16, the number of individuals with missing observations is much larger. We use two questionnaires at age 16: 'Friends and Outside the World' (five items) and 'Attitudinal Scales' (seven items). The former provides information on social behaviour during term time and the latter during leisure time. There are two versions of the Attitudinal scales: i) one administered at school during term time and ii) one administered at home after individuals finish the school year. Given that both questionnaires were administered on different dates and locations, the proportion of individuals with complete information in one questionnaire and no information in the other is large. Thus, we impute all missing observations, irrespective of their number, conditional on the individual answering all the relevant questions in the other questionnaire. This allows us to recover approximately 80% of the individuals with missing information within either the Friends and Outside the World Questionnaire or the Attitudinal Scales.

[26] We compare performance among different types of imputation methods such as median/mode/mean, multiple imputation (predictive mean matching/polynomial regression), and K-nearest neighbours (KNN, euclidean/hamming distance method) according to the characteristics of the variables (continuous/categorical). We observe that a non-parametric imputation method such as iterated random forests outperforms parametric methods as we use a mixture of numerical and categorical variables throughout the study. Moreover, random forests are robust to noisy data as they build in feature selection, unlike other methods such as KNN. This characteristic eases our concerns about meaningless data biasing our predicted imputed values, given the large number of variables in our analysis.

Table A.3: Number of Individuals with Complete, Missing, and Imputed Values by Scale/Test

	Number of items [1]	Answered at least one [2]	Answered all [3]	Missing obsv. [4]	% of imputed missing obs [5]	Total OOB error [6]
Scales/Tests at Age 10						
Cognitive Tests	8	12863	11110	1753	20.94%	30.24%
Child Behaviour Scale	42	12702	9686	3016	76.26%	59.33%
Family SES	4	13695	11850	1845	80.16%	48.27%
Self-esteem (Lawrence)	12	12662	11850	812	81.77%	40.24%
Locus of control (CARALOC)	16	12612	11713	899	80.65%	43.40%
Scales at Age 16						
Friends, Outside World and Attitudinal Scales	12	6590	4318	2272	88.73%	45.96%

Notes: Data from BCS70. The table shows the number of items per scale and the number of individuals with complete and missing values. Column [4] shows the total number of individuals with missing observations. Column [5] shows the percentage of observations that were imputed from column [4], that is, those individuals who answered all questions/tests but one within each scale. We performed a non-parametric imputation using Random Forest. Column [6] shows an estimate of the out-of-bag (OOB) imputation error by scale.

A.4 Bias Correction for the Analysis of Long-Term Outcomes

Section 4 discussed the identification and estimation of our factor model, which follows closely the approach in Heckman et al. (2013) and Bolt et al. (2021).

Section 4 also discussed how the measurement system is used to correct for measurement-error-induced attenuation in our analysis of long-term outcomes. Here we specify the precise formula used to do that.

As discussed in Section 4 we construct factor scores ω_i^S for each of our six factors ω (problems of: attention, conduct, emotion and peer relations, together with family socio-economic status and teen socialization). These factor scores can then be expressed as:

$$\omega_i^S = \omega_i + \eta_i \tag{4}$$

where $\eta_i = \kappa_\omega \sum_j \frac{\lambda_{\omega,j}}{\sigma^2_{\omega,\epsilon,j}} \epsilon_{\omega,i,j}$ is a weighted sum of item-level measurement errors, is orthogonal to the latent factor, and is assumed orthogonal to covariates of interest. κ_ω is defined in Section 4.

For the model expressed in equation (3), running OLS with $\Omega_{i,\langle a \rangle}$ replaced with the observed scores will be inconsistent because these scores are then correlated with the regression error term, which includes η_i. However, the form of the bias can be derived. We rewrite equation (3) as:

$$y_{i,t} = \Gamma\Omega^S_{i,\langle a\rangle} + \beta\mathbf{X}_{i,t} + v_{i,t} - \Gamma\bar{\eta}_i$$

where $\Omega^S_{i,\langle a\rangle}$ is the vector of observed scores, and $\bar{\eta}_i$ is the vector of measurement errors. Then, abbreviating notation, and as discussed by Heckman et al. (2013) and Bolt et al. (2021):

$$\text{plim}\begin{pmatrix}\hat{\Gamma}\\ \hat{\beta}\end{pmatrix} = \begin{pmatrix}\text{Cov}\left(\Omega^S,\Omega^S\right) & \text{Cov}\left(\Omega^S,\mathbf{X}\right)\\ \text{Cov}\left(\Omega^S,\mathbf{X}\right) & \text{Cov}\left(\mathbf{X},\mathbf{X}\right)\end{pmatrix}^{-1}\begin{pmatrix}\text{Cov}\left(\Omega,\Omega\right) & \text{Cov}\left(\Omega,\mathbf{X}\right)\\ \text{Cov}\left(\Omega,\mathbf{X}\right) & \text{Cov}\left(\mathbf{X},\mathbf{X}\right)\end{pmatrix}\begin{pmatrix}\Gamma\\ \beta\end{pmatrix} \tag{5}$$

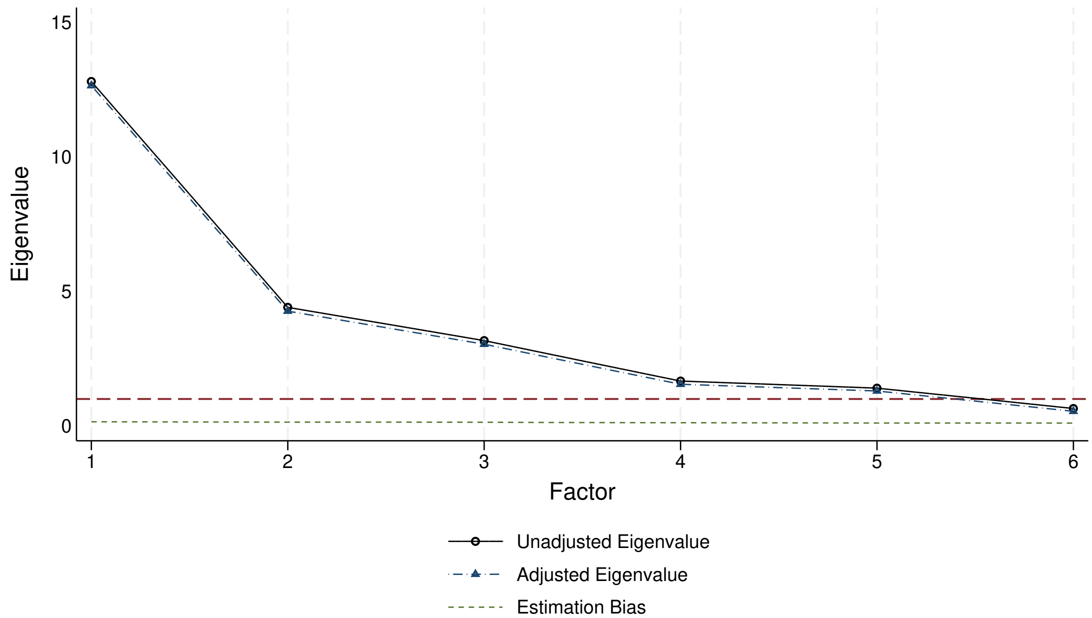
Using expression (4) above, and using the orthogonality conditions, we note that $\text{Cov}\left(\Omega,\mathbf{X}\right) = \text{Cov}\left(\Omega^S,\mathbf{X}\right)$, which is observed. Similarly $\text{Cov}\left(\Omega,\Omega\right)$ is equal to $\text{Cov}\left(\Omega^S,\Omega^S\right)$ except with diagonal elements replaced with 1s. Equation (5) allows us to identify Γ and β.

A.5 Relationship of Our Factorization with the Strength and Difficulties Questionnaire

As discussed in Section 5, our clustering of items is based on a data-informed dedicated factor analysis. We also discussed that our assignment of items bears resemblance to the scales used in the Strength and Difficulties Questionnaire (SDQ). In fact some of the allocation of items differs from that in the SDQ, as does the precise wording of the items, and is worth detailing explicitly here. Table B.2 shows abbreviations of the SDQ items in the first column, together with their corresponding scale. Each row of columns two to five then show the closest matching items in the BCS70 data. The second row, for example, shows a close match between item wording, but some small differences that are are easily noticeable: the SDQ Hyperactivity scale includes a single item covering 'fidgety or squirmy', which maps closest to our two retained items 'hums' and 'rhythmic tapping'. Columns two to five of Table B.2 also display the factor to which the BCS70 items are assigned in our factorization. As discussed in Section 5, the correspondece of SDQ scales to our factors is close, but not one-to-one. In particular SDQ Hyperactivity lines up closest to our attention factor, even though a few items are closely worded to BCS70 items that appear in conduct.

B Detailed Factorization Results

Figure B.1: Eigenvalues from EFA of Age-10 Skills, Final Iteration



Notes: Data from BCS70. The figure shows unadjusted and adjusted eigenvalues from a factorization with retained items after several iterations of an exploratory factor analysis (see Table 1). Adjusted eigenvalues are obtained by using Horn's parallel analysis for factor analysis. This procedure involves performing factor analyses on both the actual data and samples generated randomly, extracting eigenvalues from each, and comparing them to ensure that the appropriate number of factors have been retained.

Table B.1: EFA of Age-10 Skills by Gender: Final Iteration

	Attention		Conduct		Emotion		Peer		Cognition	
	Males	**Females**	**Males**	**Females**	**Males**	**Females**	**Males**	**Females**	**Males**	**Females**
Cannot complete tasks	**0.808**	**0.75**	-0.052	-0.053	-0.038	-0.061	0.05	0.029	-0.015	-0.024
Fails to finish tasks	**0.8**	**0.76**	-0.023	-0.041	-0.025	-0.018	0.05	0.026	0.009	-0.01
Easily distracted	**0.771**	**0.752**	0.167	0.165	0.022	0.052	-0.127	-0.124	-0.037	-0.044
Fails to show perseverance	**0.753**	**0.715**	0.031	0.009	-0.048	-0.051	0.024	0.03	-0.074	-0.049
Fails to pay attention in class	**0.722**	**0.754**	0.051	0.058	-0.081	-0.085	0.058	0.02	-0.098	-0.052
Daydreaming	**0.696**	**0.648**	-0.133	-0.12	0.123	0.124	0.104	0.102	0.041	0.018
Bored in class	**0.682**	**0.681**	0.17	0.163	-0.022	0	0.06	0.051	-0.025	0.004
Forgetful on complex task	**0.601**	**0.584**	-0.023	-0.006	0.199	0.186	-0.03	0.018	-0.204	-0.182
Cannot concentrate on task	**0.57**	**0.594**	0.019	-0.003	0.053	0.04	-0.014	0.031	-0.082	-0.062
Shows lethargic behaviour	**0.502**	**0.494**	-0.044	-0.018	0.135	0.139	0.273	0.268	-0.001	0.01
Displays outbursts of temper	-0.089	-0.07	**0.812**	**0.799**	0.037	0.034	0.084	0.052	-0.032	-0.015
Teases other children	-0.008	-0.021	**0.8**	**0.814**	-0.133	-0.124	0.021	0.037	-0.013	-0.051
Bullies other children	-0.04	-0.088	**0.769**	**0.824**	-0.151	-0.132	0.129	0.11	-0.071	-0.062
Quarrels with other kids	0.03	0.079	**0.767**	**0.74**	-0.039	0.004	0.166	0.125	-0.062	-0.033
Changes mood quickly	0.017	0.046	**0.71**	**0.708**	0.232	0.255	-0.005	-0.037	0.000	0.011
Interferes with others	0.278	0.214	**0.656**	**0.68**	-0.115	-0.099	-0.007	-0.019	-0.012	-0.025
Excitable and impulsive	0.067	0.088	**0.653**	**0.621**	0.214	0.219	-0.341	-0.328	0.023	0.015
Destroys belongings	0.063	0.069	**0.636**	**0.593**	-0.037	-0.104	0.134	0.178	-0.023	-0.014
Complains about things	0.046	0.118	**0.625**	**0.605**	0.087	0.115	0.05	-0.011	-0.008	0.011
Restless or over-active behv.	0.242	0.189	**0.599**	**0.6**	0.216	0.228	-0.26	-0.205	0.051	0.011
Sullen or sulky	0.023	0.065	**0.582**	**0.626**	0.094	0.09	0.247	0.224	-0.05	0.025
Easily frustrated	0.129	0.151	**0.544**	**0.545**	0.21	0.195	-0.073	-0.057	-0.041	0.019
Hums or makes odd vocals	0.215	0.152	**0.49**	**0.463**	0.056	-0.052	-0.077	0.043	0.019	-0.003
Rhythmic tapping in class	0.24	0.164	**0.47**	**0.441**	0.062	-0.015	-0.083	0.022	0.035	0.004
Worried	-0.016	0.004	0.078	0.095	**0.839**	**0.832**	0.004	-0.002	-0.022	-0.018
Anxious	-0.043	-0.054	-0.021	-0.005	**0.733**	**0.714**	0.151	0.207	-0.031	-0.05
Behaves nervously	0.094	0.074	-0.011	-0.043	**0.724**	**0.717**	0.072	0.088	-0.045	-0.074
Afraid of new situations	0.188	0.2	-0.155	-0.17	**0.534**	**0.563**	0.096	0.102	-0.172	-0.134
Fussy	-0.079	0.012	0.266	0.349	**0.526**	**0.515**	0.017	-0.098	0.081	0.062
Child is not friendly	0.135	0.118	0.152	0.147	0.097	0.059	**0.729**	**0.729**	-0.02	-0.045
Child is not popular with peers	0.159	0.148	0.196	0.213	0.067	0.025	**0.704**	**0.697**	-0.021	-0.048
Introvert	-0.024	-0.059	-0.34	-0.316	0.335	0.321	**0.584**	**0.594**	-0.01	-0.034
Child is not cooperative	0.131	0.144	0.35	0.334	-0.006	-0.023	**0.539**	**0.494**	-0.03	-0.001
Rather solitary	-0.002	-0.023	0.032	0.033	0.287	0.246	**0.532**	**0.568**	0.099	0.061
Reading	-0.071	-0.083	-0.015	0.016	0.001	0.01	0.006	0.006	**0.82**	**0.813**
BAS words	0.068	0.062	-0.003	-0.018	0.021	-0.003	-0.012	0.01	**0.806**	**0.793**
Pictorial (PLC)	0.114	0.084	-0.047	-0.049	0.006	-0.019	0.017	0.009	**0.788**	**0.752**
Maths	-0.123	-0.082	0.02	0.024	-0.035	-0.019	0.006	0.011	**0.766**	**0.77**
BAS simil	0.068	0.074	0.008	-0.026	-0.008	-0.014	0.024	0.003	**0.753**	**0.757**
BAS matrix	-0.054	0.012	-0.038	-0.04	0.007	0.021	0.036	-0.012	**0.637**	**0.647**
Spelling	-0.148	-0.225	0.061	0.067	-0.048	-0.009	-0.008	0.017	**0.597**	**0.536**
BAS digits	-0.057	-0.044	0.008	0.049	-0.041	-0.023	-0.005	0.005	**0.423**	**0.437**
Cronbach's alpha	0.926	0.916	0.931	0.929	0.847	0.848	0.832	0.815	0.861	0.854

Notes: Data from BCS70. The table compares factor loadings of retained items between males and females (3386 and 3566 observations, respectively) obtained from an exploratory factor analysis (EFA) using a polychoric correlation matrix and oblique quartimin rotation. Items are sorted in descending order of loadings within each construct for males. Cronbach's alpha coefficients for the internal consistency of the set of retained items within each factor are also reported.

Table B.2: Comparison with Labels from Strength and Difficulties Questionnaire

SDQ Scales	Factorization: Attention	Factorization: Conduct
Hyperactivity		
(i) Restless, overactive, cannot stay still for long		(i) Restless, over-active behaviour;
(ii) Constantly fidgeting or squirming		(ii) Hums or makes odd vocals; Rhythmic tapping in class
(iii) Easily distracted, concentration wanders	(iii) Easily distracted; Becomes bored during class; Child is daydreaming; Fails to pay attention in class; Fails to show perseverance; Shows lethargic behaviour	
(iv) Thinks things out before acting (reversed)		(iv) Excitable and impulsive
(v) Sees tasks through to the end, good attention span (reversed)	(v) Cannot complete tasks; Cannot concentrate on task; Forgetful on complex task; Fails to finish tasks	
Conduct problems		
(i) Often has temper tantrums or hot tempers		(i) Displays outbursts of temper; Changes mood quickly; Sullen or sulky
(ii) Generally obedient, usually does what adults request (reversed)		(ii) Destroys belongings; Easily frustrated; Complains about things
(iii) Often fights with other children or bullies them		(iii) Teases other children; Bullies other children; Quarrels with other kids; Interferes with others
(iv) Often lies or cheats		
(v) Steals from home, school or elsewhere		

Table B.2: Continued

SDQ Scales	Factorization	
	Emotion	**Peer**
Emotional problems		
(i) Often complains of headaches, stomach-aches or sickness	(i) Fussy	
(ii) Many worries, often seems worried	(ii) Worried	
(iii) Often unhappy, down-hearted or tearful		
(iv) Nervous or clingy in new situations, easily loses confidence	(iv) Afraid of new situations; Anxious; Behaves nervously	
(v) Many fears, easily scared		
Peer problems		
(i) Rather solitary, tends to play alone		(i) Rather solitary; Introvert
(ii) Has at least one good friend (reversed)		(ii) Child is not friendly
(iii) Generally liked by other children (reversed)		(iii) Child is not popular with peers
(iv) Picked on or bullied by other children		
(v) Gets on better with adults than with other children		
Prosocial		
(i) Considerate of other people's feelings		
(ii) Shares readily with other children (treats, toys, pencils etc.)		
(iii) Helpful if someone is hurt, upset or feeling ill		
(iv) Kind to younger children		
(v) Often volunteers to help others (parents, teachers, other children)		(v) Child is not cooperative

Notes: Data from BCS70. The table pairs items with similar definitions from 25 items in the Strengths & Difficulties Questionnaire (SDQ) and 42 items in the Child Development Questionnaire (BCS70). The 25 SDQ items comprise 5 scales (hyperactivity, conduct problems, emotional problems, peer problems, and prosocial) of 5 items each, which are then compared to items within the 4 socio-emotional skills derived in this paper.

Table B.3: EFA of Age-10 Skills for Restricted Item Set: Final Iteration

Items	**Externalising**	**Internalising**	**Cognition**	**Relationship to Main Factorization**
Bullies other children	**0.896**	-0.118	0.011	Conduct Problems
Quarrels with other kids	**0.809**	0.073	-0.013	Conduct Problems
Destroys belongings	**0.793**	0.042	-0.017	Conduct Problems
Restless or over-active behv.	**0.785**	0.060	0.000	Conduct Problems
Squirmy and fidgety	**0.760**	0.031	-0.123	Attention Problems*
Face or body twitches	**0.422**	0.267	0.035	Conduct Problems*
Worried	-0.030	**0.807**	-0.011	Emotion Problems
Unhappy or tearful	0.275	**0.671**	0.047	Emotion Problems*
Afraid of new situations	-0.205	**0.669**	-0.233	Emotion Problems
Rather solitary	-0.029	**0.625**	0.105	Peer Problems
Fussy	0.164	**0.518**	0.109	Emotion Problems
Child is not popular with peers	-0.231	**-0.513**	0.064	Peer Problems
Reading	-0.060	0.012	**0.839**	Cognition
Maths	-0.014	-0.042	**0.805**	Cognition
BAS words	0.027	0.019	**0.771**	Cognition
Pictorial (PLC)	0.009	0.028	**0.732**	Cognition
BAS simil	0.044	0.005	**0.728**	Cognition
BAS matrix	-0.086	0.029	**0.637**	Cognition
Spelling	-0.040	-0.045	**0.630**	Cognition
BAS digits	-0.003	-0.030	**0.452**	Cognition
Cronbach's alpha	0.788	0.719	0.857	

Notes: Data from BCS70. Items for the construction of externalizing and internalizing behaviours are obtained from the harmonized teacher questionnaire (Rutter Questionnaire). Table shows the final iteration of an exploratory factor analysis using these items. The last column shows the relationship between externalising and internalising behaviours with our 4 socio-emotional skills. Cronbach's alpha coefficients for the internal consistency of the set of retained items within each factor are also reported.
*Items with low loadings (<0.4) or high cross-loadings (>0.75) that were dropped after several iterations in our main factorization using 50 items from the Child Development Questionnaire (see Table 1).

Table B.4: MTMM Analysis of Age-10 Social and Interpersonal Skills

		Teacher				Mother				Equal corr
		Attention	Conduct	Emotion	Peer	Attention	Conduct	Emotion	Peer	Prob > χ^2
Teacher	Attention	$\alpha = 0.79$								
	Conduct	0.57*	$\alpha = 0.91$							
	Emotion	0.33*	0.32*	$\alpha = 0.71$						
	Peer	0.30*	0.29*	0.42*	$\alpha = 0.62$					
Mother	Attention	**0.38***	**0.25***	0.10*	0.11*	$\alpha = 0.79$				0.00
	Conduct	**0.20***	**0.22***	0.03	0.09*	0.55*	$\alpha = 0.83$			0.21
	Emotion	-0.01	-0.05*	**0.15***	**0.07***	0.21*	0.33*	$\alpha = 0.59$		0.00
	Peer	0.05*	0.04	**0.08***	**0.18***	0.17*	0.31*	0.30*	$\alpha = 0.31$	0.00

Notes: Data from BCS70. Table shows a multitrait-multimethod analysis of age-10 social and interpersonal skills. The dataset comprises 19 aggregated measures that are close in definition reported by the pupils' teacher and mother (3 attention, 11 conduct, 3 emotion and 2 peer). Sample size for mother-teacher comparison is 6705. The diagonal shows Cronbach's alphas within each construct. The remaining cells contain Pairwise correlation coefficients (* p <.01, Bonferroni-adjusted significance level). The last column shows p-values associated with a chi-square test of equality of correlation between constructs in bold.

Table B.5: EFA of Age-10 Skills, Including Mindset: First Iteration

Items	Attention	Conduct	Emotion	Peer	Self-esteem	LOC	Cognition
Easily distracted	**0.787**	0.130	0.024	-0.113	-0.059	0.009	-0.046
Fails to finish tasks	**0.769**	-0.026	-0.020	0.063	0.005	-0.041	-0.003
Cannot complete tasks	**0.762**	-0.046	-0.049	0.074	-0.004	-0.019	-0.036
Fails to show perseverance	**0.717**	0.017	-0.064	0.060	-0.055	-0.004	-0.088
Fails to pay attention in class	**0.715**	0.058	-0.082	0.071	-0.023	-0.015	-0.100
Bored in class	**0.673**	0.165	-0.012	0.068	-0.013	-0.058	-0.010
Daydreaming	**0.654**	-0.121	0.115	0.122	-0.019	-0.047	0.027
Forgetful on complex task	**0.609**	-0.029	0.214	-0.003	0.005	-0.017	-0.208
Cannot concentrate on task	**0.579**	0.005	0.041	0.030	-0.022	-0.013	-0.082
Squirmy and fidgety	0.522	0.395	0.122	-0.188	-0.019	-0.041	0.051
Shows lethargic behaviour	**0.469**	0.004	0.150	0.283	0.042	-0.099	0.017
Confused with diffic. tasks	0.467	-0.080	0.387	-0.025	-0.012	-0.006	-0.265
Displays outbursts of temper	-0.057	**0.800**	0.036	0.063	-0.008	-0.015	-0.027
Bullies other children	-0.033	**0.791**	-0.128	0.094	0.035	-0.040	-0.068
Teases other children	0.029	**0.784**	-0.123	0.013	0.010	0.002	-0.038
Quarrels with other kids	0.048	**0.741**	-0.016	0.138	-0.100	0.054	-0.088
Changes mood quickly	0.024	**0.695**	0.246	-0.014	-0.047	0.019	-0.018
Destroys belongings	0.070	**0.635**	-0.027	0.127	0.070	-0.118	0.017
Interferes with others	0.287	**0.634**	-0.106	-0.024	-0.044	0.021	-0.030
Sullen or sulky	0.012	**0.624**	0.103	0.243	-0.023	-0.033	-0.028
Complains about things	0.061	**0.603**	0.113	0.016	-0.101	0.060	-0.040
Excitable and impulsive	0.126	**0.586**	0.203	-0.339	-0.058	0.062	0.008
Restless or over-active behv.	0.280	**0.560**	0.211	-0.249	-0.011	-0.018	0.062
Easily frustrated	0.158	**0.527**	0.204	-0.072	-0.025	-0.010	-0.014
Hums or makes odd vocals	0.237	**0.469**	0.027	-0.057	0.075	-0.156	0.093
Rhythmic tapping in class	0.242	**0.455**	0.054	-0.074	0.075	-0.167	0.100
Cannot negotiate child's behv.	0.272	0.320	-0.124	0.273	-0.003	-0.039	0.049
Face or body twitches	0.087	0.285	0.211	0.008	0.093	-0.140	0.085
Worried	0.007	0.065	**0.819**	0.002	-0.033	-0.002	-0.006
Behaves nervously	0.119	-0.032	**0.724**	0.066	0.037	-0.075	-0.013
Anxious	-0.032	-0.018	**0.696**	0.174	-0.025	-0.034	-0.013
Afraid of new situations	0.170	-0.173	**0.562**	0.099	-0.019	-0.018	-0.163
Fussy	-0.080	0.277	**0.545**	-0.050	-0.127	0.109	0.014
Obsessed with unimportant tasks	0.008	0.380	0.443	0.046	-0.038	0.003	-0.002
Cries for little cause	-0.045	0.322	0.409	0.081	-0.088	0.030	-0.045
Unhappy or tearful	-0.020	0.358	0.372	0.338	-0.048	-0.041	0.009
Child is not friendly	0.146	0.157	0.055	**0.704**	-0.106	-0.002	-0.033
Child is not popular with peers	0.164	0.209	0.025	**0.682**	-0.117	0.006	-0.044
Introvert	-0.046	-0.295	0.312	**0.592**	0.038	-0.097	0.016
Rather solitary	0.001	0.059	0.251	**0.535**	-0.008	-0.067	0.114
Child is not cooperative	0.149	0.356	-0.047	**0.530**	-0.062	0.004	-0.033
Child is not bold	0.009	-0.414	0.348	0.441	0.043	-0.067	-0.060
SEQ: sad, nobody to play with	0.032	0.076	-0.038	-0.023	**0.689**	-0.075	0.050
SEQ: feel lonely at school	-0.018	0.051	-0.056	-0.069	**0.670**	-0.022	-0.051
SEQ: children break friends	0.028	-0.037	0.050	-0.023	**0.627**	-0.004	0.087
SEQ: find friends, mine play with others	-0.008	0.009	0.006	-0.054	**0.620**	-0.035	0.073
SEQ: other children say nasty things	-0.029	-0.022	0.063	-0.023	**0.564**	0.084	-0.113
SEQ: people think that you tell lies	-0.037	-0.037	0.085	0.021	**0.472**	0.190	-0.096
SEQ: feel foolish when talking to teacher	0.044	0.074	-0.076	0.089	**0.429**	0.231	-0.054

Table B.5: Continued

LOC: blamed for things that aren't your fault	-0.086	-0.050	0.095	0.027	**0.425**	0.246	-0.111
SEQ: lots of things to change about yourself	-0.050	-0.003	0.040	0.030	**0.421**	0.133	-0.068
SEQ: feel foolish in front of other children	0.005	0.088	-0.054	0.066	0.382	0.175	0.021
SEQ: feel foolish when talking to parents	-0.018	0.005	0.030	0.074	0.361	0.158	0.028
SEQ: feel shy when talking to teachers	0.070	0.125	-0.103	0.070	0.352	0.118	0.040
LOC: feel sad when it's time to leave school	0.096	0.015	-0.045	-0.022	0.223	-0.194	0.200
LOC: studying for tests is a waste of time	-0.042	-0.049	0.052	-0.019	-0.010	**0.523**	-0.062
LOC: high marks just a matter of "luck"	0.033	-0.007	-0.011	-0.002	0.011	**0.507**	0.211
LOC: nice things happen is only good luck	0.099	-0.036	-0.002	0.001	0.034	**0.482**	0.206
LOC: tests are a lot of guess work	0.017	-0.017	-0.044	0.028	0.047	**0.480**	0.178
LOC: useless try in school, others are cleverer	-0.034	-0.013	-0.014	0.033	0.178	**0.471**	0.184
LOC: not worth trying, things never go well	0.040	-0.049	-0.001	0.042	0.176	**0.425**	0.106
LOC: get low marks, even when study hard	-0.141	0.066	0.010	-0.004	0.171	**0.401**	0.184
LOC: bad things, it's someone else's fault	-0.001	-0.024	0.048	-0.024	0.098	0.326	-0.073
SEQ: parents don't like to hear your ideas	-0.020	-0.024	0.048	-0.017	0.039	0.288	0.007
LOC: arguments, it's the other person's fault	0.014	0.000	0.021	-0.038	-0.018	0.190	-0.053
BAS words	0.078	-0.035	0.001	-0.002	-0.001	0.066	**0.771**
Reading	-0.149	-0.012	0.023	0.004	-0.009	0.046	**0.756**
Pictorial (PLC)	0.082	-0.066	-0.005	0.010	-0.005	0.028	**0.746**
Maths	-0.124	0.021	-0.015	0.000	0.054	0.016	**0.739**
BAS simil	0.064	-0.028	-0.010	0.008	-0.009	0.045	**0.726**
BAS matrix	-0.095	-0.042	0.035	0.001	-0.004	-0.013	**0.607**
Spelling	-0.250	0.059	-0.012	0.010	-0.008	0.090	**0.490**
BAS digits	-0.087	0.027	-0.024	0.011	0.004	0.059	0.384
LOC: people good no matter what	0.079	-0.003	-0.041	0.062	-0.182	-0.067	0.315
LOC: imp. make friends when angry	0.050	0.009	-0.029	0.004	0.123	0.113	0.280
LOC: surprised when you've done well	-0.050	0.034	-0.036	0.048	0.188	0.254	0.256
LOC: wishing make good things happen	0.064	-0.009	-0.032	0.040	0.097	-0.020	0.242
LOC: planning don't make things better	0.049	-0.038	0.010	-0.005	-0.029	0.064	0.096
Cronbach's alpha	0.925	0.931	0.847	0.823	0.711	0.667	0.857

Notes: Data from BCS70. The table reports factor loadings obtained from an exploratory factor analysis (EFA) of the main sample (6952 observations) using a polychoric correlation matrix and oblique quartimin rotation. Items in bold are retained after several iterations. We construct a dedicated measurement system adding self-esteem as an additional factor to our main specification, see equation (1). Table C.10 shows estimates for self-esteem on selected outcomes of interest. Cronbach's alpha coefficients for the internal consistency of the set of retained items within each factor are also reported.

Table B.6: EFAs of Family Background and Teen Socialization: First Iterations

Age10		**Age16**	
Items	**Family Backg.**	**Items**	**Teen Socialization**
Parental social status	**0.830**	**Go to a friend's house**	**0.785**
Parent in manager post	**0.717**	**Go out with friends**	**0.783**
Parental qualifications	**0.681**	**Have friends round to house**	**0.715**
Family income	**0.634**	**Spend time at friend's homes (school term)**	**0.686**
		Stay at home with friends (school term)	**0.633**
		Go out with friends do nothing special (school term)	**0.601**
		Hang about the street	**0.559**
		Go with friends to cinema, disco etc. (school term)	**0.466**
		Go to a youth club/organization	0.303
		Number of friends	0.258
		Go out with brothers/sisters	0.107
		Go to a meeting/political club	-0.018
Eigenvalues	2.068		3.673
Cronbach's alpha	0.712		0.790

Notes: Data from BCS70. The table reports factor loadings obtained from an exploratory factor analysis (EFA) of the main sample for family background (6952 observations) and age-16 sample for teen socialization (3377 observations) using a polychoric correlation matrix and oblique quartimin rotation. Items in bold are retained after several iterations and used in our dedicated measurement system. Eigenvalues and Cronbach's alpha coefficients for the internal consistency of the set of retained items within each factor are also reported.

Table B.7: Loadings from Confirmatory Factor Analysis: Main Sample

Items	Loadings	Items	Loadings
Attention Problems		**Emotion Problems**	
Easily distracted	0.85	Worried	0.87
Bored in class	0.80	Anxious	0.80
Fails to pay attention in class	0.79	Behaves nervously	0.80
Fails to show perseverance	0.78	Afraid of new situations	0.67
Fails to finish tasks	0.77	Fussy	0.51
Cannot complete tasks	0.76		
Forgetful on complex task	0.75	**Peer Problems**	
Daydreaming	0.66	Child is not friendly	0.91
Cannot concentrate on task	0.65	Child is not popular with peers	0.91
Shows lethargic behaviour	0.61	Child is not cooperative	0.68
		Rather solitary	0.56
		Introvert	0.45
Conduct Problems		**Cognition**	
Quarrels with other kids	0.80	Reading	0.86
Interferes with others	0.79	Maths	0.83
Displays outbursts of temper	0.78	BAS words	0.74
Teases other children	0.77	Pictorial (PLC)	0.72
Changes mood quickly	0.77	BAS simil	0.70
Bullies other children	0.75	BAS matrix	0.66
Restless or over-active behv.	0.73	Spelling	0.66
Sullen or sulky	0.68	BAS digits	0.46
Complains about things	0.68		
Easily frustrated	0.67	**Family SES**	
Destroys belongings	0.67	Parental social status	0.83
Excitable and impulsive	0.66	Parental qualifications	0.69
Hums or makes odd vocals	0.58	Family income	0.59
Rhythmic tapping in class	0.58	Parent in manager post	0.50
Tucker-Lewis index (TLI)		0.988	
Comparative fit index (CFI)		0.804	
Std root-mean-sq-residual (RMSR)		0.068	
Root mean sq error of approx (RMSEA)		0.101	

Notes: Data from BCS70. The table shows estimated factor loadings from a confirmatory factor analysis (CFA) for the measurement system described in equation (1) using a sample of 6952 observations. Incremental and absolute measures of goodness of fit are also reported: TLI (Tucker and Lewis, 1973) and CFI (Bentler, 1990) have a scale from zero to one, with values close to one indicating a good fit. RMSR (Joreskog and Sorbom, 1986) and RMSEA (Browne and Cudeck, 1992; Steiger, 1990) also range from zero to one, with values close to zero indicating a good fit.

Table B.8: Loadings from CFA: Sample with Age-16 Characteristics

Items	Loadings	Items	Loadings
Teen Socialization		**Emotion Problems**	
Go to a friend's house	0.75	Worried	0.87
Have friends round to my house	0.70	Behaves nervously	0.81
Go out with friends	0.69	Anxious	0.79
Spend time at friends' homes (school term)	0.64	Afraid of new situations	0.68
Stay at home with friends (school term)	0.59	Fussy	0.53
Go out with friends do nothing special (school term)	0.47		
Go with friends to cinema, disco etc. (school term)	0.41		
Hang about the streets	0.37	**Peer Problems**	
		Child is not friendly	0.91
Attention Problems		Child is not popular with peers	0.91
Easily distracted	0.85	Child is not cooperative	0.68
Bored in class	0.79	Rather solitary	0.58
Fails to pay attention in class	0.77	Introvert	0.47
Forgetful on complex task	0.76		
Fails to show perseverance	0.76		
Fails to finish tasks	0.75	**Cognition**	
Cannot complete tasks	0.73	Reading	0.85
Daydreaming	0.67	Maths	0.82
Cannot concentrate on task	0.63	BAS words	0.74
Shows lethargic behaviour	0.62	Pictorial (PLC)	0.71
		BAS simil	0.70
Conduct Problems		BAS matrix	0.65
Quarrels with other kids	0.79	Spelling	0.63
Changes mood quickly	0.78	BAS digits	0.44
Displays outbursts of temper	0.77		
Interferes with others	0.77		
Teases other children	0.75	**Family SES**	
Restless or over-active behv.	0.74	Parental social status	0.83
Bullies other children	0.74	Parental qualifications	0.71
Complains about things	0.69	Family income	0.61
Sullen or sulky	0.69	Parent in manager post	0.49
Destroys belongings	0.67		
Easily frustrated	0.67		
Excitable and impulsive	0.66		
Hums or makes odd vocals	0.55		
Rhythmic tapping in class	0.57		
Tucker-Lewis index (TLI)		0.769	
Comparative fit index (CFI)		0.781	
Std root-mean-sq-residual (RMSR)		0.065	
Root mean sq error of approx (RMSEA)		0.063	

Notes: Data from BCS70. The table shows estimated factor loadings from a Confirmatory Factor Analysis (CFA) for the measurement system described in equation (1) adding teen socialization as an additional latent construct and using a sample of 3377 observations. Incremental and absolute measures of fit are also reported: TLI (Tucker and Lewis, 1973) and CFI (Bentler, 1990) have a scale from zero to one, with values close to one indicating a good fit. RMSR (Joreskog and Sorbom, 1986) and RMSEA (Browne and Cudeck, 1992; Steiger, 1990) also range from zero to one, with values close to zero indicating a good fit.

Table B.9: Correlation Matrix: Age-10 Skills and Other Background Characteristics

	Atte	**Cond**	**Emot**	Peer	Exte	Inte	SEst	Cogn	FSES	Soci	YSch
Attention	1.00										
Conduct	0.59	1.00									
Emotion	0.39	0.29	1.00								
Peer	0.46	0.38	0.45	1.00							
Externalising	**0.60**	**0.89**	0.27	0.35	1.00						
Internalising	0.45	0.41	**0.84**	**0.69**	0.38	1.00					
Self-Esteem	-0.19	-0.16	-0.17	-0.23	-0.15	-0.21	1.00				
Cognition	-0.48	-0.18	-0.25	-0.25	-0.21	-0.25	0.24	1.00			
Family SES	-0.19	-0.11	-0.10	-0.10	-0.09	-0.10	0.14	0.39	1.00		
Socialization	0.02	0.02	-0.06	-0.09	0.02	-0.08	0.01	-0.06	-0.06	1.00	
Years School	-0.32	-0.15	-0.13	-0.14	-0.15	-0.13	0.16	0.50	0.42	-0.13	1.00

Notes: Data from BCS70. Factor scores are obtained from a confirmatory factor analysis (CFA) of a dedicated measurement system, see equation (1). The table shows the correlation matrix among factor scores reported in this study and years of schooling. Externalising and internalising behaviours are factor scores obtained from a dedicated measurement system using items from the harmonized teacher questionnaire (see Table B.3).

C Additional Results Quoted in the Main Paper

Table C.1: Determinants of Working Hours

	All [1]	Males [2]	Females [3]	q-values [2]-[3]
Attention	0.001	0.002	-0.004	0.529
	[0.005]	[0.004]	[0.010]	
Conduct	0.011***	0.008**	0.013**	0.443
	[0.004]	[0.003]	[0.007]	
Emotion	-0.017***	-0.007**	-0.024***	0.020
	[0.003]	[0.003]	[0.007]	
Peer	0.004	-0.007**	0.017***	0.001
	[0.004]	[0.003]	[0.007]	
Cognition	0.009**	-0.005	0.023***	0.001
	[0.004]	[0.003]	[0.008]	
Family SES	0.001	0.007**	-0.010	0.021
	[0.004]	[0.003]	[0.006]	
Yrs School	0.011***	-0.002*	0.027***	0.000
	[0.002]	[0.001]	[0.003]	
Backg. Controls	X	X	X	
N	6952	3386	3566	
Individual-years	23,451	11,404	12,047	

Notes: Data from BCS70. Each column reports error-corrected estimates from a regression of the log monthly working hours on standardized socio-emotional skills, cognition, and family SES obtained from our dedicated measurement system, see equation (1). All specifications are controlled for number of siblings, dummies for first child, no dad at birth, teenage mother, year and region fixed effects. Specification [1] also includes controls for gender and gender-by-year. Standard errors in brackets are estimated from 250 bootstrap replications clustered at the individual level: ***p < .01, **p < .05, *p < .10. FDR q-values are adjusted p-values of gender differences for multiple hypothesis testing at outcomes of interest.

Table C.2: Determinants of Labour Supply: Extensive Margin

	All [1]	**Males** [2]	**Females** [3]
Attention	-0.014***	-0.001	-0.028***
	[0.005]	[0.006]	[0.008]
Conduct	-0.003	-0.017***	0.013**
	[0.004]	[0.005]	[0.006]
Emotion	-0.003	-0.003	-0.002
	[0.004]	[0.004]	[0.006]
Peer	-0.007**	-0.010**	-0.004
	[0.003]	[0.004]	[0.006]
Cognition	0.018***	0.022***	0.013**
	[0.004]	[0.006]	[0.007]
Family SES	0.007*	0.001	0.012**
	[0.004]	[0.005]	[0.006]
Yrs School	0.009***	0.003**	0.015***
	[0.001]	[0.002]	[0.002]
Backg. Controls	X	X	X
N	8162	4014	4145
Individual-years	34,613	16,278	18,335

Notes: Data from BCS70. The table shows measurement-error-corrected estimates from a LPM of whether an individual is employed (employee or self-employed) on standardized socio-emotional skills, cognition, and family socio-economic status. The sample comprises all survey participants from 1996 to 2016 with complete information at age 10. All specifications control for: number of siblings, dummies for first child, no dad at birth, teenage mother, year and region fixed effects. Column [1] also includes controls for gender and gender-by-year. Standard errors in brackets are estimated from 250 bootstrap replications clustered at the individual level: ***p < .01, **p < .05, *p < .10.

Table C.3: Determinants of Occupational Sorting by Gender

	Males			Females			q-values		
	Physical	**Analytical**	**Interpers**	**Physical**	**Analytical**	**Interpers**	**Physical**	**Analytical**	**Interpers**
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[1]-[4]**	**[2]-[5]**	**[3]-[6]**
Attention	0.088***	-0.050**	-0.090***	0.024	-0.065***	-0.028	0.087	0.642	0.089
	[0.026]	[0.022]	[0.026]	[0.027]	[0.022]	[0.025]			
Conduct	-0.021	0.022	0.062***	0.037*	0.076***	0.043**	0.042	0.024	0.479
	[0.021]	[0.016]	[0.020]	[0.019]	[0.017]	[0.018]			
Emotion	-0.019	-0.019	-0.031	-0.050**	-0.008	0.009	0.278	0.602	0.119
	[0.020]	[0.015]	[0.019]	[0.020]	[0.015]	[0.017]			
Peer	-0.033*	-0.045***	0.003	0.011	-0.023	-0.027	0.122	0.334	0.254
	[0.020]	[0.016]	[0.019]	[0.020]	[0.017]	[0.018]			
Cognition	-0.087***	0.136***	0.096***	-0.043*	0.143***	0.096***	0.164	0.794	0.997
	[0.022]	[0.021]	[0.022]	[0.022]	[0.018]	[0.023]			
Family SES	-0.089***	0.066***	0.085***	0.002	0.071***	0.042**	0.001	0.852	0.118
	[0.020]	[0.020]	[0.020]	[0.020]	[0.016]	[0.019]			
Yrs School	-0.079***	0.087***	0.081***	0.017**	0.133***	0.113***	0.000	0.000	0.004
	[0.007]	[0.007]	[0.007]	[0.008]	[0.007]	[0.009]			
Backg. Controls	X	X	X	X	X	X			
N	3386	3386	3386	3566	3566	3566			
Individual-years	11404	11404	11404	12047	12047	12047			

Notes: Data from BCS70 and O*NET. Each column reports error-corrected estimates from a regression of standardized occupational task intensities (see Table 5 notes) on standardized socio-emotional skills, cognition, and family socio-economic status. All specifications control for: number of siblings, dummies for first child, no dad at birth, teenage mother, year and region fixed effects. Standard errors in brackets are estimated from 250 bootstrap replications clustered at the individual level: ***p < .01, **p < .05, *p < .10. FDR q-values are adjusted p-values of gender differences for multiple hypothesis testing at outcomes of interest.

Table C.4: Determinants of Teen Characteristics by Gender

	Males			Females		
	Teen Socialization	**Attitudes Business**	**Mental Health**	**Teen Socialization**	**Attitudes Business**	**Mental Health**
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**
Attention	0.007	-0.183***	0.029	0.049	-0.120**	0.003
	[0.052]	[0.065]	[0.058]	[0.048]	[0.060]	[0.045]
Conduct	0.080*	-0.007	-0.028	0.051	0.033	-0.050
	[0.045]	[0.052]	[0.050]	[0.039]	[0.050]	[0.042]
Emotion	-0.093**	0.032	-0.134***	-0.041	-0.001	-0.029
	[0.040]	[0.043]	[0.039]	[0.034]	[0.039]	[0.032]
Peer	-0.134***	0.093*	-0.035	-0.127***	0.020	-0.051*
	[0.038]	[0.051]	[0.041]	[0.032]	[0.042]	[0.030]
Cognition	-0.028	0.145***	0.034	-0.110***	-0.095*	0.011
	[0.047]	[0.056]	[0.049]	[0.042]	[0.050]	[0.044]
Family SES	-0.084**	0.056	0.013	-0.003	-0.057	0.058*
	[0.040]	[0.054]	[0.041]	[0.033]	[0.042]	[0.031]
Backg. Controls	X	X	X	X	X	X
N	1563	868	1310	2188	1189	1872

Notes: Data from BCS70 and O*NET. Each column reports error-corrected estimates from a regression of standardized age-16 variables (see Table 7 notes) on standardized socio-emotional skills, cognition, and family socio-economic status. All specifications control for: number of siblings, dummies for first child, no dad at birth, teenage mother, year and region fixed effects. Standard errors in brackets are estimated from 250 bootstrap replications: ***p < .01, **p < .05, *p < .10.

Table C.5: Earnings Determinants, Including Career Interests

	[1]	[2]	[3]	[4]	[5]	[6]
Business	0.037***					
	[0.010]					
Practical		0.064***				
		[0.016]				
Living			-0.016			
			[0.010]			
Communication				-0.004		
				[0.011]		
Art					-0.045***	
					[0.011]	
Caring						-0.028**
						[0.012]
Attention	-0.052***	-0.059***	-0.055***	-0.058***	-0.060***	-0.058***
	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]
Conduct	0.049***	0.049***	0.050***	0.050***	0.049***	0.049***
	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]
Emotion	-0.031***	-0.029**	-0.029**	-0.030**	-0.030***	-0.028**
	[0.012]	[0.011]	[0.012]	[0.012]	[0.011]	[0.011]
Peer	-0.006	-0.002	-0.005	-0.004	-0.003	-0.005
	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]
Cognition	0.040**	0.038**	0.042**	0.041**	0.037**	0.039**
	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]
Family SES	0.061***	0.060***	0.061***	0.060***	0.060***	0.060***
	[0.014]	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]
Yrs School	0.044***	0.044***	0.044***	0.044***	0.044***	0.043***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Backg. Controls	X	X	X	X	X	X
N	1847	1847	1847	1847	1847	1847
Individual-years	6729	6729	6729	6729	6729	6729

Notes: Data from BCS70 and O*NET. Each column reports error-corrected estimates from a regression of log real monthly earnings as the dependent variable on standardized scores of 6 occupational attitudes from the JIIG-CAL Questionnaire in wave 1986, standardized socio-emotional skills, cognition, and family socio-economic status. All specifications control for: gender, gender-by-year, number of siblings, dummies for first child, no dad at birth, teenage mother, year and region fixed effects. Standard errors in brackets are estimated from 250 bootstrap replications clustered at the individual level: ***p < .01, **p < .05, *p < .10.

Table C.6: Determinants of Adult Health

	Prob.Drinking AUDIT score [1]	Freq. Drinking [2]	Freq. Smoking [3]	Mental Health [4]	Job Satisfaction [5]	Life Satisfaction [6]	Well-being (WEMWB) [7]	GHQ-12 [8]	Num of Arrests [9]
Attention	0.022	0.036*	0.101***	-0.009	-0.037**	-0.047**	0.018	-0.001	0.059*
	[0.028]	[0.019]	[0.021]	[0.017]	[0.018]	[0.019]	[0.028]	[0.026]	[0.032]
Conduct	0.070***	0.012	0.081***	-0.004	0.039***	0.019	0.006	-0.027	0.111***
	[0.022]	[0.015]	[0.017]	[0.014]	[0.013]	[0.014]	[0.021]	[0.022]	[0.028]
Emotion	-0.023	-0.016	-0.076***	-0.040***	-0.006	-0.008	-0.041**	-0.044**	-0.093***
	[0.021]	[0.013]	[0.015]	[0.012]	[0.011]	[0.012]	[0.018]	[0.019]	[0.017]
Peer	-0.046**	-0.036**	-0.004	-0.045***	-0.045***	-0.074***	-0.027	-0.024	0.013
	[0.022]	[0.015]	[0.017]	[0.013]	[0.011]	[0.014]	[0.020]	[0.019]	[0.019]
Cognition	0.035	0.118***	0.029	0.016	-0.048***	-0.026*	0.045**	-0.018	-0.001
	[0.025]	[0.017]	[0.019]	[0.015]	[0.015]	[0.015]	[0.022]	[0.022]	[0.021]
Family SES	0.008	0.114***	0.009	0.031**	0.014	0.032**	0.058***	-0.009	-0.036**
	[0.022]	[0.015]	[0.016]	[0.014]	[0.013]	[0.013]	[0.020]	[0.019]	[0.017]
Yrs School	0.004	0.022***	-0.081***	0.022***	0.003	0.022***	0.029***	0.005	-0.042***
	[0.007]	[0.006]	[0.006]	[0.005]	[0.005]	[0.005]	[0.007]	[0.008]	[0.006]
Backg. Controls	X	X	X		X	X	X	X	X
N	4183	6841	6939	6820	6557	6874	4183	4963	4963
Individual-years	6,327	19,269	23,405	19107	16,512	19,667	6,407	4963	4963

Notes: Data from BCS70. The table shows measurement-error-corrected estimates from regressions of problematic behaviours, general health and life/job satisfaction on standardized socio-emotional skills, cognition, and family socio-economic status. Total Alcohol-Use Disorders Identification Test (AUDIT) is a standardized 20-point score available for years 2012 and 2016. Frequency of drinking is a Likert scale from “never" to “4 or more times per week" available for all years but 2008. Frequency of smoking is a Likert scale from “never" to “every day" available for all years. Mental health is a standardized Malaise score (reversed) within each year for 24 questions (years 1996, 2000) and 9 questions (years 2004, 2012, 2016). Job satisfaction is a Likert scale from “very dissatisfied" to “very satisfied" available for all years but 2004 and 2008. Life satisfaction is a Likert scale from “completely dissatisfied" to “completely satisfied" available for all years but 2008. The Warwick Edinburgh Mental Well-Being Scale is a standardized 70-point score available for years 2012 and 2016. General Health is a standardized total score for 12 questions available in 2016. Number of arrests is a self-reported question asked in 2000. All specifications control for: gender, gender-by-year, number of siblings, dummies for first child, no dad at birth, teenage mother, year and region fixed effects, as appropriate for each sample. Standard errors in brackets are estimated from 250 bootstrap replications clustered at the individual level: ***p < .01, **p < .05, *p < .10.

Table C.7: Main Regressions Comparing Factorizations Pooled/Split by Gender

	Males				Females			
	Schooling		Earnings		Schooling		Earnings	
	Only Males Factorization [1]	Pooled Factorization [2]	Only Males Factorization [3]	Pooled Factorization [4]	Only Females Factorization [5]	Pooled Factorization [6]	Only Females Factorization [7]	Pooled Factorization [8]
Attention	-0.307***	-0.337***	-0.024**	-0.031***	-0.114**	-0.077	-0.036**	-0.029**
	[0.066]	[0.072]	[0.010]	[0.011]	[0.054]	[0.061]	[0.014]	[0.013]
Conduct	-0.025	-0.064	0.027***	0.028***	-0.052	-0.013	0.046***	0.045***
	[0.051]	[0.064]	[0.008]	[0.008]	[0.045]	[0.043]	[0.011]	[0.010]
Emotion	0.078	0.126**	-0.025***	-0.022***	0.034	-0.016	-0.029***	-0.033***
	[0.051]	[0.049]	[0.008]	[0.008]	[0.041]	[0.043]	[0.010]	[0.010]
Peer	0.022	0.068	-0.030***	-0.028***	0.028	-0.018	0.005	0.003
	[0.050]	[0.049]	[0.009]	[0.009]	[0.040]	[0.048]	[0.010]	[0.010]
Cognition	0.724***	0.803***	0.060***	0.044***	0.730***	0.672***	0.077***	0.075***
	[0.062]	[0.063]	[0.010]	[0.010]	[0.045]	[0.052]	[0.012]	[0.010]
Family SES	0.595***	0.543***	0.043***	0.057***	0.624***	0.668***	0.026**	0.027**
	[0.055]	[0.054]	[0.010]	[0.009]	[0.044]	[0.047]	[0.010]	[0.011]
Yrs School			0.027***	0.026***			0.075***	0.076***
			[0.003]	[0.004]			[0.005]	[0.005]
Backg. Controls	X	X	X	X	X	X	X	X
N	3386	3386	3386	3386	3566	3566	3566	3566
Individual-years			11,404	11,404			12,047	12,047

Notes: Data from BCS70. The table compares measurement-error-corrected estimates from regressions of selected outcomes of interest on standardized socio-emotional skills, cognition, and family socio-economic status obtained from separate factorizations first using gender-specific samples and second using a pooled sample. All specifications control for: number of siblings, dummies for first child, no dad at birth, teenage mother, year and region fixed effects. Specifications [1], [3], [5] and [7] repeat results from earlier tables. Standard errors in brackets are estimated from 250 bootstrap replications clustered at the individual level: ***p < .01, **p < .05, *p < .10.

Table C.8: Attachment to the BCS Survey

	All [1]	Males [2]	Females [3]
Attention	0.001	-0.061	0.081
	[0.039]	[0.051]	[0.058]
Conduct	-0.083**	-0.088**	-0.092*
	[0.032]	[0.043]	[0.048]
Emotion	0.072**	0.016	0.148***
	[0.030]	[0.040]	[0.045]
Peer	-0.036	0.014	-0.085*
	[0.032]	[0.043]	[0.046]
Cognition	0.285***	0.230***	0.364***
	[0.033]	[0.044]	[0.050]
Family SES	0.076***	0.070*	0.081*
	[0.028]	[0.037]	[0.043]
Backg. Controls	X	X	X
N	6952	3386	3566

Notes: Data from BCS70. The table shows estimates from logit regressions of whether an individual from the main sample (6952 observations) participated in all surveys from 1996 to 2016 on age-10 skills and socio-demographic characteristics. All specifications control for: number of siblings, dummies for first child, no dad at birth, teenage mother, year and region fixed effects. Specification [1] also includes controls for gender and gender-by-year. Standard errors in brackets: ***p < .01, **p < .05, *p < .10.

Table C.9: Main Regressions, with Inverse Probability Weighting

	Schooling		Earnings		Wages		Working Hours	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Attention	-0.221***	-0.216***	-0.027***	-0.025***	-0.028***	-0.027***	0.001	0.001
	[0.045]	[0.045]	[0.009]	[0.009]	[0.007]	[0.007]	[0.005]	[0.005]
Conduct	-0.037	-0.037	0.037***	0.034***	0.026***	0.024***	0.011***	0.010***
	[0.036]	[0.036]	[0.006]	[0.006]	[0.005]	[0.005]	[0.004]	[0.003]
Emotion	0.058*	0.056*	-0.029***	-0.029***	-0.012**	-0.012**	-0.017***	-0.017***
	[0.033]	[0.033]	[0.006]	[0.006]	[0.005]	[0.005]	[0.003]	[0.003]
Peer	0.025	0.020	-0.014**	-0.016**	-0.018***	-0.019***	0.004	0.003
	[0.032]	[0.032]	[0.007]	[0.007]	[0.005]	[0.005]	[0.004]	[0.004]
Cognition	0.726***	0.677***	0.060***	0.062***	0.051***	0.053***	0.009**	0.009**
	[0.036]	[0.038]	[0.007]	[0.007]	[0.006]	[0.006]	[0.004]	[0.004]
Family SES	0.610***	0.592***	0.046***	0.046***	0.037***	0.046***	0.001	0.001
	[0.032]	[0.034]	[0.007]	[0.007]	[0.002]	[0.006]	[0.004]	[0.004]
Yrs School			0.049***	0.046***	0.045***	0.036***	0.011***	0.010***
			[0.003]	[0.003]	[0.006]	[0.002]	[0.002]	[0.001]
Backg. Controls	X	X	X	X	X	X	X	X
N	6952	6953	6952	6952	6952	6952	6952	6952
Individual-years			23,451	23,451	23,451	23,451	23,451	23,451

Notes: Data from BCS70. The table compares measurement-error-corrected estimates from regressions of selected outcomes of interest on standardized socio-emotional skills, cognition, and family socio-economic status with those using inverse probability weighting (IPW). IPW are estimates from a logit regression of whether an individual from the main sample (6952 observations) participated in all surveys from 1996 to 2016 on age-10 skills and socio-demographic characteristics (see Table C.8). All specifications control for: gender, gender-by-year, number of siblings, dummies for first child, no dad at birth, teenage mother, year and region fixed effects. Standard errors in brackets are estimated from 250 bootstrap replications clustered at the individual level: ***p < .01, **p < .05, *p < .10.

Table C.10: Main Regressions, Controlling for Mindset Skills

	Schooling		Earnings		Wages		Working Hours	
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**
Self-Esteem		0.060**		0.008		0.016***		-0.008*
		[0.029]		[0.006]		[0.005]		[0.004]
Attention	-0.221***	-0.219***	-0.027***	-0.027***	-0.028***	-0.028***	0.001	0.001
	[0.045]	[0.045]	[0.009]	[0.009]	[0.007]	[0.007]	[0.005]	[0.005]
Conduct	-0.037	-0.032	0.037***	0.037***	0.026***	0.027***	0.011***	0.010***
	[0.036]	[0.036]	[0.006]	[0.007]	[0.005]	[0.005]	[0.004]	[0.004]
Emotion	0.058*	0.058*	-0.029***	-0.029***	-0.012**	-0.012**	-0.017***	-0.017***
	[0.033]	[0.033]	[0.006]	[0.006]	[0.005]	[0.005]	[0.003]	[0.003]
Peer	0.025	0.036	-0.014**	-0.012*	-0.018***	-0.015***	0.004	0.003
	[0.032]	[0.032]	[0.007]	[0.007]	[0.005]	[0.005]	[0.004]	[0.004]
Cognition	0.726***	0.716***	0.060***	0.059***	0.051***	0.049***	0.009**	0.010***
	[0.036]	[0.037]	[0.007]	[0.007]	[0.006]	[0.006]	[0.004]	[0.004]
Family SES	0.610***	0.607***	0.046***	0.045***	0.037***	0.044***	0.001	0.001
	[0.032]	[0.032]	[0.007]	[0.007]	[0.002]	[0.006]	[0.004]	[0.004]
Yrs School			0.049***	0.048***	0.045***	0.037***	0.011***	0.011***
			[0.003]	[0.003]	[0.006]	[0.002]	[0.002]	[0.002]
Backg. Controls	X	X	X	X	X	X	X	X
N	6952	6952	6952	6952	6952	6952	6952	6952
Individual-years			23,451	23,451	23,451	23,451	23,451	23,451

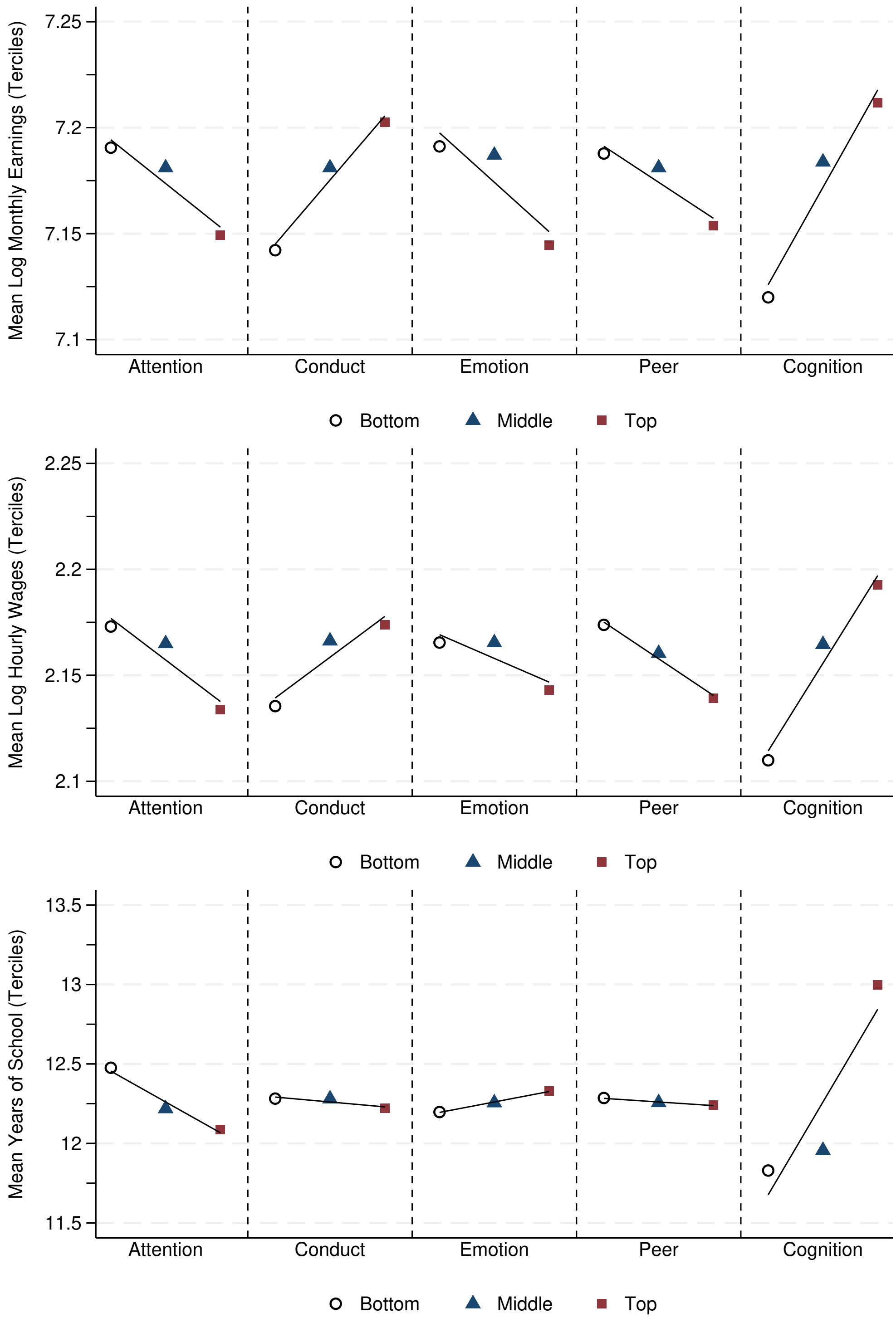
Notes: Data from BCS70. The table compares measurement-error-corrected estimates from regressions of selected outcomes of interest on standardized socio-emotional skills, cognition, and family socio-economic status with those that also account for mindset factors (self-esteem) obtained from our dedicated measurement system, see equation (1). All specifications control for: gender, gender-by-year, number of siblings, dummies for first child, no dad at birth, teenage mother, year and region fixed effects. Standard errors in brackets are estimated from 250 bootstrap replications clustered at the individual level: ***p < .01, **p < .05, *p < .10.

Table C.11: Main Regressions, Controlling for Parental Warmth

	Schooling		**Earnings**		**Wages**		**Working Hours**	
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**
Parental Warmth		0.030		0.001		-0.003		0.004
		[0.035]		[0.007]		[0.005]		[0.004]
Attention	-0.221***	-0.240***	-0.027***	-0.027***	-0.028***	-0.031***	0.001	0.004
	[0.045]	[0.046]	[0.009]	[0.010]	[0.007]	[0.008]	[0.005]	[0.005]
Conduct	-0.037	-0.037	0.037***	0.039***	0.026***	0.029***	0.011***	0.010**
	[0.036]	[0.036]	[0.006]	[0.007]	[0.005]	[0.006]	[0.004]	[0.004]
Emotion	0.058*	0.055*	-0.029***	-0.029***	-0.012**	-0.010*	-0.017***	-0.019***
	[0.033]	[0.032]	[0.006]	[0.006]	[0.005]	[0.005]	[0.003]	[0.004]
Peer	0.025	0.048	-0.014**	-0.011	-0.018***	-0.016***	0.004	0.005
	[0.032]	[0.036]	[0.007]	[0.008]	[0.005]	[0.006]	[0.004]	[0.004]
Cognition	0.726***	0.736***	0.060***	0.057***	0.051***	0.048***	0.009**	0.009**
	[0.036]	[0.039]	[0.007]	[0.008]	[0.006]	[0.006]	[0.004]	[0.004]
Family SES	0.610***	0.599***	0.046***	0.046***	0.037***	0.048***	0.001	-0.003
	[0.032]	[0.037]	[0.007]	[0.008]	[0.002]	[0.006]	[0.004]	[0.005]
Yrs School			0.049***	0.049***	0.045***	0.037***	0.011***	0.011***
			[0.003]	[0.003]	[0.006]	[0.002]	[0.002]	[0.002]
Backg. Controls	X	X	X	X	X	X	X	X
N	6952	6952	6952	6952	6952	6952	6952	6952
Individual-years			23,451	23,451	23,451	23,451	23,451	23,451

Notes: Data from BCS70. The table compares measurement-error-corrected estimates from regressions of selected outcomes of interest on standardized socio-emotional skills, cognition, and family socio-economic status with those that also account for parental warmth obtained from our dedicated measurement system, see equation (1). See footnote 24 for details on the construction of parental warmth. Cronbach's alpha for the internal consistency of the retained items is 0.73. All specifications control for: gender, gender-by-year, number of siblings, dummies for first child, no dad at birth, teenage mother, year and region fixed effects. Standard errors in brackets are estimated from 250 bootstrap replications clustered at the individual level: ***p < .01, **p < .05, *p < .10.

Figure C.1: Main Outcomes, by Tercile of Age-10 Skills



Notes: Data from BCS70. The figure shows mean log monthly earnings in the top panel, mean log hourly wages in the middle panel and mean years of school in the bottom panel by terciles of socio-emotional skills and cognition. Mean estimates for each socio-emotional skill and cognition are obtained after partialling out: the other socio-emotional skills (cognition), family socio-economic status, gender, gender-by-year, number of siblings, dummies for first child, no dad at birth, teenage mother, year and region fixed effects.