The Economic Value of *Breaking Bad*: Misbehavior, Schooling and the Labor Market*

Nicholas W. Papageorge†
Department of Economics, Johns Hopkins University

Victor Ronda‡
Department of Economics, Johns Hopkins University

Yu Zheng§
Department of Economics and Finance, City University of Hong Kong
Department of Economics, European University Institute

April 8, 2016

Abstract: Prevailing research argues that childhood misbehavior in the classroom is bad for schooling and, presumably, bad overall. In contrast, we argue that childhood misbehavior captures underlying non-cognitive skills that are potentially valuable in the labor market. We follow work from psychology and summarize observed classroom misbehavior as two underlying latent factors. Next, we estimate a model of educational attainment and earnings, allowing the impact of each of these two factors to vary by outcome. We show the first evidence that one of the factors driving childhood misbehavior, discussed in psychological literature as externalizing behavior (and linked, for example, to aggression), does indeed reduce educational attainment, but also increases earnings. Typically, the skills comprising human capital are seen as enhancing productivity. In contrast, our findings illustrate how the same skill can be productive in some economic contexts and counter-productive in others. Policies designed to promote human capital accumulation can therefore have mixed effects or even negative economic consequences. This is especially concerning for policies that target non-cognitive skill formation aimed at children or adolescents, for whom non-cognitive skills are relatively malleable.

Keywords: Labor, Education, Non-Cognitive Skills
JEL Classification: J10 J20 I20

*We gratefully acknowledge helpful comments from: Seth Gershenson, Barton Hamilton, Hans von Kippersluis, Patrick McAlvanah, Robert Moffitt, Albert Park and Richard Spady along with seminar participants at the City University of Hong Kong, Tinbergen Institute, the Brookings Institution, Georgetown University, Universtiy of Western Ontario, European University Institute and the Econometric Society World Congress. The usual caveats apply.

†[Corresponding author] papageorge@jhu.edu.
‡ronda@jhu.edu.
§yuzheng@cityu.edu.hk

1 Introduction

Economists generally recognize that human capital consists of multiple skills that drive educational and labor market outcomes. An early contribution is Willis and Rosen (1979), who distinguish between academic and manual skill. More recently, a burgeoning literature in economics has extended the concept of human capital to incorporate non-cognitive skills, such as perseverance and grit (Heckman and Rubinstein, 2001).[1] It is not controversial that returns to the skills comprising human capital can differ across sectors. Some skills are more productive in schooling versus work or in one occupation over another. For example, to explain career choices, Willis and Rosen (1979) emphasize variation in the returns across occupations to manual versus academic skill.[2]

Despite potential differences in returns, however, the skills that constitute human capital are typically seen as enhancing productivity—both in school and on the labor market. This is likely true for cognition and for many non-cognitive skills, such as grit, which captures goal setting (Duckworth et al., 2007). However, this view overlooks how some components of human capital could be productive in some economic contexts but counter-productive in others. If so, then policies designed to promote human capital accumulation could have mixed effects or even negative economic consequences. This is especially concerning for policies that target non-cognitive skill formation aimed at children or adolescents, for whom non-cognitive skills have been shown to be relatively malleable (Heckman and Kautz, 2013).

In this paper, we examine a widely-studied pair of non-cognitive skills, both of which are identified from teachers' reports of misbehavior or maladjustment among schoolchildren. The skills are known as *externalizing behavior* and *internalizing behavior*.[3] Externalizing behavior is linked to aggression and hyperactivity. Internalizing behavior captures anxiety, depression, shyness, unassertiveness and fearfulness (Ghodsian, 1977; Duncan and Magnuson, 2011; Duncan and Dunifon, 2012). Using a longitudinal data set from Britain, the National Child Development Survey (NCDS), we estimate an econometric model relating childhood misbehavior to educational attainment and labor market outcomes. We approximate schooling, hours or work and wages using linear-in-parameters equations and we model correlation across equations as unobserved heterogeneity in the form of three latent factors: externalizing and internalizing behavior, capturing non-cognitive skills, and cognition. We also estimate the model separately for males and females. Our main finding is that, for both genders, one of the factors underlying observed classroom misbehavior, externalizing

[1] Excellent summaries of this research are found in Borghans et al. (2008) and Almlund et al. (2011).

[2] This point has its origins in Roy's model of selection into occupations (Roy, 1951).

[3] Regarding the nomenclature: "externalizing behavior" and "internalizing behavior" describe the latent factors interpreted as two "non-cognitive skills" identified using childhood misbehavior.

behavior, lowers educational attainment, but also carries a wage premium. In other words, we demonstrate that a penchant for *breaking bad* can be good.[4]

Whereas previous work has recognized variation in skill prices across economic sectors, our findings on externalizing behavior go further, demonstrating that a single skill can be productive in some economic contexts and counter-productive in others. Identifying a skill that raises wages, but lowers educational attainment is a particularly striking illustration since it runs counter to the typical view of ability bias in estimates of the returns to education (Becker, 1967). Generally, the presumption is that the unobserved skills leading to success in education would also promote earnings.[5] In line with this assumption, among individuals in our sample, we demonstrate that schooling predicts higher earnings; that internalizing behavior predicts lower education attainment and lower earnings; and that cognition predicts higher degrees and higher earnings. In contrast, externalizing behavior has mixed effects. Despite its negative impact on schooling, it is also associated with higher wages for males and females and with more hours in the labor market for females.[6]

Mixed effects of externalizing behavior suggest that a productive labor market skill may be easily overlooked or difficult to detect or foster since it is not productive in school. Our findings also point to a mismatch between the types of skills promoted in school and the skills that are valuable on the labor market. This point echoes findings in Heckman and Rubinstein (2001), who show that the GED is a "mixed" signal of productivity since it is taken by high school dropouts with low non-cognitive skill. As a result, educational attainment or certification is a potentially flawed signal of a future worker's productivity. An informative signal should be designed to accurately reflect all skills that are productive in the labor market. Similarly, in our context, if externalizing behavior carries an earnings premium, then at the very least it should not carry an education penalty.

More generally, our findings illustrate that broadening our understanding of what constitutes human capital, which the literature on non-cognitive skills has done, also opens up the possibility that some human capital investments can have negative economic returns in some

[4] According to www.urbandictionary.com the definition of the term *breaking bad* is to "challenge conventions" or to "defy authority". *Breaking Bad* is also the title of an American television show in which the protagonist is an unsuccessful chemist who reveals a striking talent for producing illicit drugs. The show offers an extreme example of how certain skills or behaviors may lead to low productivity in one sector and high productivity in another.

[5] There are a number of exceptions. For example Card (2012) shows that IV estimates could lead to larger coefficients on education in wage equations. The argument is based on heterogeneity in treatment effects coupled with the particular group for whom the IV affects attendance.

[6] Several studies have examined the relationship between these two behaviors to better known measures like the "Big 5" personality traits. Evidence suggests that externalizing behavior is related to conscientiousness, agreeableness, and openness to new experience, while internalizing behavior is mostly related to neuroticism (Ehrler, Evans, and McGhee, 1999; Almlund et al., 2011).

sectors. For example, despite the positive returns to educational attainment, investments designed to curb or eliminate childhood misbehavior may be ill-conceived or short-sighted since a subset of children who misbehave may be expressing non-cognitive skills that are valuable in the labor market. This is not a hypothetical concern since school districts are increasingly poised to begin using high-stakes tests to evaluate students, teachers and schools based on character or non-cognitive skills (West et al., 2015).

Having demonstrated that externalizing has mixed effects on economic outcomes, we next consider two possible interpretations of our findings. The first is that we have isolated a skill that is unproductive in school, but productive in the labor market. An alternative explanation is that externalizing behavior drives a set of decisions or outcomes that also affect earnings. One obvious example is selection into employment. Suppose unproductive high-externalizing individuals select out of the labor market. Then, estimates of positive labor market returns to externalizing behavior could be an artifact of differential sorting, which would undermine the idea that a valuable component of human capital is counterproductive in some economic contexts. In a series of sensitivity analyses, we therefore assess how externalizing behavior predicts labor supply, occupation choice, work experience, fertility and partnership. While we show evidence that externalizing behavior is strongly related to many of these economic outcomes, we also demonstrate that these relationships do not drive our main finding that externalizing behavior, despite being unproductive at school, is productive in the labor market.

The externalizing premium in the labor market has not been recognized in previous literature on the economic consequences of childhood misbehavior. We identify several key reasons why. First, most earlier literature on the long run effects of childhood misbehavior takes for granted that externalizing is broadly unproductive, focussing instead on school-related outcomes (Bertrand and Pan, 2013). This may be due to data limitations since linking childhood misbehavior to labor market outcomes requires a long panel beginning with a sample of children. However, even studies using the NCDS data have not linked externalizing behavior to earnings. For example, Farmer (1993, 1995) show that males who display high levels of externalizing behavior leave school earlier, obtain fewer qualifications, and begin their careers in lower social class positions. However, neither study considers actual performance in the labor market.[7] Second, many studies use a single, aggregated measure of misbehavior. Segal (2013) shows that misbehavior during the eighth grade can have a negative impact on future earnings even after controlling for schooling attainment and Sciulli

[7]Nor do these studies control for internalizing behavior, which means they may suffer from omitted variables bias if the two are correlated. Other work from psychology and sociology uses the NCDS data to examine selection into occupations. Jackson (2006) shows that having low levels of internalizing behavior is an important predictor of managerial occupations.

(2016) demonstrates that adult employment outcomes are negatively related to childhood maladjustment. Also using the NCDS data set, Fronstin, Greenberg, and Robins (2005) show that a single measure of misbehavior predicts lower earnings in adulthood. Using the NCDS data set, we are able to replicate the basic result that aggregated misbehavior predicts lower earnings. However, we go on to show that key implications change dramatically once we recognize that misbehavior reflects two distinct factors with potentially different returns in the labor market.

Another reason we depart from earlier work is rooted in differences in returns to skills across socioeconomic groups. Heckman, Pinto, and Savelyev (2013) show that an early childhood intervention (the Perry Preschool Program) raised earnings and that about 20% of this rise is attributable to a reduction in externalizing behavior. In contrast, we find that, for a 1958 British cohort, externalizing behavior raises earnings. Exploring this difference leads us to our third set of findings, which is to demonstrate differences in the returns to externalizing behavior across socioeconomic groups. In particular, we consider a sub-sample of the NCDS British cohort that is selected to mimic the financially disadvantaged group studied in Heckman, Pinto, and Savelyev (2013). We show that, among individuals who grew up in poverty, externalizing behavior carries no significant earnings premium. This finding is in line with Lundberg (2013), who demonstrates that the payoff to non-cognitive skills is context-dependent and may vary by socioeconomic status. One possible reason is selection into criminality (Aizer, 2009; Heckman, Pinto, and Savelyev, 2013). However, we find that differential sorting into police involvement does not appear to drive differences in returns to externalizing behavior across socioeconomic groups. Therefore, we cannot rule out the possibility that some skills are simply priced differently in the labor market depending on an individual's background. This possibility is troubling if it means that individuals who are already disadvantaged are excluded from realizing the full returns to their skills. More broadly, our findings on group differences imply further difficulties in evaluating human capital investments involving children's non-cognitive skills since the returns to skills can differ not only by the economic context in question, but also by socioeconomic status.

The rest of the paper is organized as follows. In Section 2, we introduce the data set, discuss measurements of misbehavior that identify externalizing and internalizing behavior and conduct a preliminary data analysis. In Section 3, we describe the econometric framework and estimation. In Section 4, we present results. Section 5 concludes.

2 Data and Preliminary Analysis

In this section, we introduce the data set used in this paper and conduct a preliminary data analysis. First, we provide details on the NCDS and on how we construct the analytic sample. Second, we discuss how classroom behavior is used to identify two latent factors: externalizing and internalizing behavior. Third, we report summary statistics on education, labor market outcomes and childhood misbehavior in the classroom. Fourth, we provide estimates from a preliminary econometric model relating childhood misbehavior with schooling and earnings. In particular, we demonstrate that once we treat externalizing and internalizing behaviors separately, externalizing behavior is associated with higher earnings even though it also predicts lower schooling attainment.

2.1 The National Child Development Study

The NCDS is an ongoing longitudinal survey that follows the universe of individuals born in the same week in 1958 in Great Britain. The data set contains information on physical and educational development, wages, employment, family life, well-being, social participation and attitudes. The NCDS is particularly well-suited for our study since it documents teachers' reports of classroom misbehavior for a large sample of children and then follows these children through adulthood. Therefore, the data set allows us to relate misbehavior in elementary school to educational attainment along with labor market outcomes. To date, there have been eight surveys to trace all the members of the cohort still living in Great Britain. Surveys occurred when subjects were born and when they were aged 7 (1965), 11, 16, 23, 33, 42 and 50 (2008).

We focus on information gathered at birth and the first five sweeps, covering ages 7 to 33. The NCDS initially contained 18,555 births. At the second wave, 15,356 of the original sample remained as respondents and by the fifth survey, at age 33, 11,407 individuals remained. In constructing our analytic sample, we keep respondents with valid information on test scores and classroom misbehavior at age 11 and educational attainment at age 33, which leaves us with 9,511 individuals. We drop individuals with missing information on relationship status, fertility and employment status at age 33. We also drop individuals with missing information on their employment history or who are reported as employed but have missing information on earnings at age 33.[8] The resulting analytic sample has complete information on 7,324 individuals, of whom 3,612 are males and 3,712 are females.[9]

[8]We drop individuals when there is missing information on one of the key outcome variables used in our analysis. However, we impute data for missing control variables, including parents' education and occupation.

[9]To assess whether sample attrition drives our main results, we compare our final sample to the sample

2.2 Classroom Misbehavior and Non-Cognitive Skills

In our main econometric analysis, we model unobserved heterogeneity as three underlying factors. The first two factors are the non-cognitive skills: externalizing behavior and internalizing behavior. The third factor is cognition, which is identified using math and reading test scores. In this section, we describe how inventories completed by teachers describing student behavior in the classroom are used to identify the non-cognitive skills.

When a child in the sample was 11-years-old, the child's teacher was asked to complete an inventory listing the child's behaviors in the classroom. The teacher was given a list of roughly 250 descriptions of specific behaviors and asked to underline the items which best fit the child. These descriptions include statements such as: "too timid to be naughty"; "brags to other children"; "normally honest with school work"; "adopts extreme youth fashions"; and "has stolen money". Completed inventories were then used to compute scores on a set of ten maladjustment syndromes, known as the Bristol Social Adjustment Guide or *BSAG* maladjustment syndromes. The syndromes were first defined in Stott, Sykes, and Marston (1974). They are: hostility towards adults, hostility towards children, anxiety for acceptance by adults, anxiety for acceptance by children, restlessness, inconsequential behavior, writing off adults and adults standards, depression, withdrawal and unforthcomingness. The syndromes have been used since their introduction in Stott, Sykes, and Marston (1974) to assess the psychological development of children.[10] They have also been externally validated in the sense that the inventories used to measure the ten syndromes are positively correlated with a range of other measurements of social maladjustment from teachers, professional observers, parents and peers (Achenbach, McConaughy, and Howell, 1987).

Using principle components factor analysis, Ghodsian (1977) showed that the ten BSAG maladjustment syndrome variables could be described by two distinct latent factors.[11] Ghodsian (1977) also proposed a mapping between the measurements and the two factors, which gives a meaningful interpretation to each one. The mapping assigns each observed maladjustment syndrome to one of the two factors. According to the mapping, the first factor corresponds to anxious, aggressive, outwardly-expressed or *externalizing behavior* and includes maladjustment syndromes such as "hostility towards adults" and "restlessness". The

of individuals observed at age 11, to which we refer as the "full sample". We report the summary statistics of the full sample in Tables S1 and S2 in Appendix A. Compared to the full sample, our analytic sample is slightly less educated, more likely to be self-employed and more likely to have a partner at age 33. However, none of these differences are statistically significant.

[10] Unfortunately, the NCDS does not provide access to the original completed inventories. We only have access to the computed maladjustment syndrome scores.

[11] In Appendix A, we use our sample to confirm that two independent factors adequately describe data on the ten BSAG maladjustment syndromes.

second factor corresponds to withdrawn, inhibited or *internalizing behavior* and includes maladjustment syndromes such as “depression”.[12] In Table 1, we list each factor along with the maladjustment syndromes used to identify it.[13] The two factors have been studied extensively by psychologists researching child development and, of late, by some economists (Blanden, Gregg, and Macmillan, 2007; Aizer, 2009; Agan, 2011; Heckman, Pinto, and Savelyev, 2013).[14]

Though there is some debate on the key assumptions underlying the structure of the mapping between maladjustment syndromes and underlying factors, in our analysis, we generally follow Ghodsian (1977).[15] We use 10 BSAG maladjustment syndrome variables to identify two latent factors, externalizing and internalizing behavior. We also assume dedicated measurements, which means that each measurement is related to only one unobserved factor, even though this assumption is not required (Rao and Sinharay, 2006).[16] Following Ghodsian (1977) has the advantage of making our results comparable to other work studying childhood misbehavior and economic outcomes. This includes work using the NCDS data set studying externalizing and internalizing behaviors (Farmer, 1993, 1995; Jackson, 2006). It also includes research using different samples since the division of misbehavior into these two factors now extends to other data sets, including the CNLSY and the PSID (Yeung, Linver, and Brooks-Gunn, 2002; Agan, 2011).

[12]In Appendix A, we confirm that a standard rotation method reveals that variables such as “hostility towards adults and children” and “inconsequential behavior” represent outwardly-expressed behaviors and are strongly related to the first factor in the factor analysis. This factor represents externalizing behavior. Observed maladjustment syndromes such as “depression,” “unforthcomingness” and “withdrawal” represent inwardly expressed behaviors and are strongly related to the second factor in the factor analysis.

[13]Syndromes we do not use are “miscellaneous nervous symptoms, “miscellaneous symptoms”, “appearance”, “attendance” and “health factors”. In results available upon request, we repeat our analysis using “miscellaneous nervous symptoms” and “miscellaneous symptoms” and find no significant differences in results.

[14]Both Aizer (2009) and Agan (2011) study how externalizing behavior is linked to anti-social and criminal activity. For general surveys on the use of externalizing and internalizing behaviors, see Duncan and Magnuson (2011) and Duncan and Dunifon (2012).

[15]For example, while traditional factor analytic methods determine the number of unobserved factors in one step and the mapping in a second step, newer Bayesian methods estimate the number of factors and their mapping to the measurement system simultaneously (Conti et al., 2014). In Appendix A, we discuss issues surrounding factor analytic methods for childhood misbehavior in greater detail.

[16]The exception is “writing off adults and adult standards”, which could represent an outwardly or inwardly expressed behavior and is statistically related to both factors. In this case, we again follow previous work and allow the variable to be related to both factors (Ghodsian, 1977; Shepherd, 2013). We also perform robustness checks where we assign the ambiguous variables to either factor. Results remain largely unchanged.

2.3 Summary Statistics

In this section, we present summary statistics on educational attainment, labor market outcomes and childhood misbehavior. For individuals in our sample, schooling is compulsory until age 16. Thereafter, students can leave school without any qualifications (no certificate), study for an exam to obtain a Certificate of Secondary Education (CSE) or study towards obtaining the Ordinary Levels (O-Levels), where the latter are more academically demanding.[17] If students decide to stay in school at age 16, another set of examinations is available, the Advanced Levels (A-Levels). Students who are successful in their A-Levels are able to continue to higher education and obtain either a higher-education diploma (after two years of study) or a bachelor's degree (after three years of study). At the postgraduate level, students can obtain a higher degree: Master of Philosophy (MPhil) or Doctor of Philosophy (PhD). In summary, individuals in our sample can sort into six mutually exclusive schooling levels: no certificate, CSE, O-Levels, A-Levels, higher education (including diploma and bachelors) or higher degree (including MPhil and PhD).

Summary statistics on education, labor market and other adult outcomes are found in Table 2. Perhaps most striking are large gender differences, which reflects the fact that the analytic sample is a 1958 cohort. According to the table, females in our sample are less educated than the males. Roughly half of the males obtain O-Level qualifications or less, whereas roughly two-thirds of the females do. We also find large gender differences in employment and, conditional on employment, hourly wages and hours worked. Conditional on working, hourly wages average about 7.64 pounds for males and 5.46 pounds for females and weekly earnings average 329 pounds for males and 162 pounds for females, all measured in 1991 pounds. Differences in educational attainment only offer a partial explanation for labor market disparities. In Figure 1, we show that, at each education level, males have higher wages, work longer hours and earn more. Despite these differences, the relative returns to schooling are higher for females than for males (Panel 1(d) in the same figure). Females with a higher degree earn 3 times as much as females with no formal education, while for males this ratio is 1.75. This may reflect gender differences in how individuals sort into schooling based on their cognitive and non-cognitive skills or differences in skill prices across genders, both of which our econometric analysis will account for.

Another factor explaining differences in labor market outcomes is fertility. According to Table 2, females and males in our sample are equally likely to have a partner, though females are roughly 20% more likely to have children. A stark gender difference emerges

[17] CSEs and O-Levels were replaced by the General Certificates of Secondary Education (GCSE) in 1986 after individuals in our sample had finished their schooling.

if we compare the earnings of males and females with and without children. Females with children work many fewer hours than those without children. For males, having children in the household predicts no drop in labor supply. These patterns can be observed in Figure 2. Accordingly, our econometric analysis will consider the role of partnership and fertility in mitigating the gender-specific relationship between non-cognitive skills and earnings. In general, large gender differences in schooling and labor market outcomes suggest that we should allow the parameters of our econometric model to vary for males and females.

In Table 3, we present averages for each BSAG variable separately by gender. Values of the BSAG variables ranges from 0 to 15, with a higher value indicating a higher prevalence of a particular maladjustment syndrome. These scores were constructed using the teacher responses to particular statements about the student's behavior. The means are usually low due to a clustering around zero and fairly low values in general. Nonetheless, there are significant differences across gender. In general, females appear to misbehave less frequently than males. Specifically, males score higher for each of the BSAG variables except for "anxiety for acceptance by adults". For example, for "inconsequential behavior" and "anxiety for acceptance by children", the average for males is roughly double that of females. Gender differences in misbehavior are consistent with earlier findings documented in Great Britain (Duncan and Magnuson, 2011; Duncan and Dunifon, 2012) and in the U.S. (Bertrand and Pan, 2013).

2.4 Misbehavior, Schooling and Earnings

In our main econometric analysis, we jointly estimate the mapping from unobserved factors to observed BSAG maladjustment syndrome variables with the impact of these factors on outcomes. However, for our preliminary analysis conducted here, we construct measures for externalizing and internalizing behaviors by simply summing the BSAG variables associated with each factor according to Table 1 and then including the sums as additional regressors in models where outcomes are schooling categories and earnings. We refer to these as "crude" models since summing up scores likely inflates measurement error and ignores correlation across factors. We provide estimates from the crude model to compare our findings with previous work and to demonstrate that main results, in particular mixed effects of externalizing, are not driven by the factor analytic methods used to estimate the measurement system in our main econometric analysis.

We start by estimating an ordered probit model to explain educational attainment. The outcome variable is one of the six possible schooling levels.[18] Formally, defining s_i^* as a latent

[18]Our results are robust to the specification of the educational model. The main message remains when

variable determining schooling, we estimate regressions of the following form:

$$s_i^* = E_i\psi^{\mathbf{E}} + I_i\psi^{\mathbf{I}} + C_i\psi^{\mathbf{C}} + X_i'\beta_s + e_i^S \tag{1}$$

where observed schooling $s_i = s$ if $\mu_L^s \leq s_i^* < \mu_H^s$ and μ_L^s and μ_H^s are the particular bounds for schooling level s. E_i and I_i are the measures of externalizing and internalizing behaviors based on a simple summation of the BSAG scores. Similarly, C_i is based on the sum of the reading and math test scores listed in Table 1. Here, and elsewhere, we normalize our measures of cognitive and non-cognitive skills with mean equal to 0 and variance equal to 1. Finally, X_i is a vector of covariates and e_i^S is a normally distributed disturbance.

Estimates of equation (1) are presented in Table 4 for varying sets of covariates X_i. Column [1] contains an indicator for being female and a single measure of misbehavior, obtained by summing E_i and I_i for each individual. Aggregating misbehavior into a single variable allows us to compare our results to earlier research that relates childhood misbehavior to economic outcomes, but which ignores how childhood misbehavior is driven by two separate factors, reflecting two distinct non-cognitive skills. We find that misbehavior predicts lower educational attainment. In Column [2], we add cognition C_i, which is associated with higher education. Including cognition decreases the magnitude of the negative coefficient on misbehavior from -0.37 to -0.14, which suggests strong correlation in measurements of cognition and childhood behavior. In Columns [3] and [4], we again address misbehavior and schooling with and without cognition, though here we separate misbehavior into externalizing and internalizing behavior. Both non-cognitive skills predict lower educational attainment and the inclusion of cognition decreases the magnitude of the coefficients by over half. In Column [5], we assess the robustness of estimated coefficients on non-cognitive skills to the inclusion of a number of controls, including parents' education, father's social class and whether the mother is working. As expected, higher parental education and occupation are positively related to a higher educational attainment. Coefficients on the three skills, however, remain largely unchanged. Finally, we estimate the schooling model separately for males (Column [6]) and females (Column [7]). We show that the negative effects of externalizing are larger for males (-0.12 versus -0.62). For females, internalizing has a larger effect (-0.90 versus -0.36). Cognition has a slightly larger coefficient for females. Importantly, both non-cognitive skills predict less education, while cognition predicts higher educational attainment even when we estimate the crude model separately by gender.

We perform a similar analysis for earnings, regressing log weekly earnings at age 33,

---

we use multinomial probit model instead.

conditional on being employed, onto measures of non-cognitive skills.[19] Defining y_i as log earnings at age 33 for individual i, we estimate OLS regressions of the following form:

$$y_i = E_i\phi^{\mathbf{E}} + I_i\phi^{\mathbf{I}} + C_i\phi^{\mathbf{C}} + X_i'\beta + e_i^Y \tag{2}$$

where cognitive and non-cognitive skills are defined as in equation (1) and e_i^Y is an iid disturbance.[20] The results from OLS regressions for varying sets of regressors are found in Table 5. Column [1] contains estimates using the single aggregated measure of misbehavior obtained by summing E_i and I_i. We find that aggregate misbehavior is associated with lower earnings, which is in line with previous research (Segal, 2013). Column [1] suggests that a one-standard-deviation rise in aggregated misbehavior is associated with a 10.5% decline in earnings at age 33. In Column [2], we add cognition to the regression. A one-standard-deviation rise in cognition predicts a 20.5% increase in earnings. Further, adding cognition lowers the coefficient on aggregated misbehavior to 2.8%. This sharp decline in the magnitude of the coefficient means that our measures of misbehavior are related to our measures of cognition. Our main econometric analysis explicitly treats observables as correlated measurements of underlying factors and also permits correlation among the latent factors capturing cognition and non-cognitive skills.

Results on misbehavior change dramatically, however, when we view childhood misbehavior as reflecting two distinct factors. In Columns [3]-[6] of Table 5, we regress log earnings onto E_i and I_i separately. Beginning with Column [4], where we also condition on cognition, gender and a London indicator, we find that externalizing behavior predicts higher earnings. In other words, externalizing behavior, as a non-cognitive skill, appears to carry an earnings premium. Adding schooling, we find that higher degrees predict higher earnings (Column [5]). Moreover, the positive coefficient on externalizing rises once we control for educational attainment, which makes sense since adding schooling helps to control for how externalizing could lower earnings through its negative impact on schooling. Next, we add fertility, partnership, experience and occupation (Column [6]). All controls are positively related to earnings with the exception of number of children for females. After adding these controls, the coefficient on externalizing rises once again, which suggests that the association between externalizing and earnings might work through its relationship with other lifecycle outcomes, such as fertility. We explore this possibility explicitly when assessing mechanisms

[19] Conditioning on employment raises the possibility that the preliminary results are driven by compositional effects, which we address in Section 4.4. In particular, we assess whether the positive association between externalizing behavior and earnings can be explained by high-externalizing and low productive individuals selecting into unemployment.

[20] We include a London indicator to account for possible earnings differences arising from cost-of-living. Omitting it does not affect results.

and selection in Section 4.4. Finally, in all models from Columns [4]-[8], cognition continues to predict higher earnings while internalizing behavior is associated with lower earnings.

We also run the earnings regression separately for males and females. We find the externalizing earnings premium is more pronounced for females than for males (see Columns [7] and [8] for males and females, respectively). In terms of the magnitude, once we control for educational attainment, partnership and fertility, the coefficient on externalizing behavior for females is comparable to the coefficient on cognition. Gender differences in coefficients may reflect true heterogeneity in returns, but could also reflect instability of the measurement of the two factors. In our main empirical analysis, we account for the second possibility by estimating the measurement system mapping latent factors to measurements of misbehavior separately by gender.

Taken together, crude model results presented in Tables 4 and 5 provide preliminary evidence of our main result. A non-cognitive skill that is productive on the labor market is not productive in school. It is also worth highlighting that, according to Table 5, the coefficient on externalizing is positive whether or not we control for schooling. An alternative possibility would be that externalizing behavior predicts higher earnings only after we have controlled for its negative impact on schooling. That the coefficient is positive in both cases means that, in terms of earnings, externalizing behavior has a positive net return. We now turn to the specification of our main econometric framework, which treats observed classroom behavior as mis-measurements of underlying factors.

3 Measurement Error Model and Inference

Before describing the main econometric model to be estimated, we discuss some key shortcomings of our preliminary analysis. Until now, we simply summed up BSAG maladjustment syndrome variables assigned to each underlying skill. This means we did not account for differences in explanatory power of each measurement or correlation across measurements. This can inflate measurement error, increasing attenuation bias. In what follows, we factor analyze the data on childhood classroom behavior, which means we treat each BSAG variable as a mis-measurement of one of the underlying factors. Factor analysis reduces measurement error and maps underlying factors to observed variables according to the explanatory power of each variable. Second, in our crude models, we estimated equations for schooling and earnings separately. In what follows, the equations describing the relationship between skills, schooling and labor market outcomes are estimated jointly with equations describing how underlying skills map into BSAG variables. Joint estimation reduces estimation error.

3.1 Description of the Model

There are three latent skills affecting education and labor market outcomes: externalizing behavior, internalizing behavior and cognition. Each skill is measured from a set of variables with measurement error (Table 1). We denote the k-th measurement of skill $j \in \{1, 2, 3\}$ for individual i with gender $n \in \{0, 1\}$ as m_{ijkn}, where $n = 1$ denotes male and $n = 0$ denotes female. m_{ijkn} is specified as:

$$m_{ijkn} = \overline{m}_{jk} + \alpha_{jkn} f_{ij} + \varepsilon_{ijkn} \tag{3}$$

where $\overline{m}_{jk}$ is the mean for that measurement for the whole sample, which does not vary by gender, f_{ij} is the value of latent skill j for individual i, α_{jkn} is the factor loading of latent skill j on the k-th measurement of that skill, which can vary by gender, and ε_{ijkn} is an error term capturing mis-measurement.[21] The latent factors f_{ij} are drawn from a joint normal distribution with a probability density function f^M, the parameters of which can vary by gender:[22]

$$\begin{pmatrix} f_{i1} \\ f_{i2} \\ f_{i3} \end{pmatrix} \sim N \left(\begin{pmatrix} \mu_{1,n} \\ \mu_{2,n} \\ \mu_{3,n} \end{pmatrix}, \begin{bmatrix} \sigma_{11,n} & \sigma_{12,n} & \sigma_{13,n} \\ \sigma_{12,n} & \sigma_{22,n} & \sigma_{23,n} \\ \sigma_{13,n} & \sigma_{23,n} & \sigma_{33,n} \end{bmatrix} \right) \tag{4}$$

Further, the model assumes that the latent skills are independent of measurement errors, or $cov(f_{ij}, \varepsilon_{ijkn}) = 0$, $\forall k$. The latent skill j' affects the measurement of the latent skill j only through its correlation with the skill j, or $cov(m_{ijkn}, f_{ij'}|f_{ij}) = 0$, for $j \neq j'$ and all k.[23]

We approximate the schooling problem with a linear-in-parameters ordered probit model, so that the probability that agent i chooses education level $s \in \{1, ..., 6\}$ is given by:

$$\mathrm{P}_i(s) = \Phi_s \left(\mu_s + X_{i,S}\beta_S + \sum_{j=1}^{3} \alpha_{j,S} f_{ij} \right) - \Phi_{s-1} \left(\mu_{s-1} + X_{i,S}\beta_S + \sum_{j=1}^{3} \alpha_{j,S} f_{ij} \right) \tag{5}$$

where μ_s is the cutoff for each schooling choice and where $\mu_0 = -\inf$ and $\mu_6 = \inf$. $X_{i,S}$ is the vector of observable characteristics that affect the schooling decision and β_S is the vector

[21] This setup allows us to compare the latent skill mean across genders.

[22] The results are robust to allowing for more flexible distributional assumptions on the measurement errors. In particular, we have permitted mixed normal distributions with two components and obtain qualitatively similar results.

[23] The only exception is "writing off adults and adult standards", which depends on both externalizing and internalizing behaviors.

of returns associated with $X_{i,S}$. $X_{i,S}$ contains a number of variables that are excluded from other equations: whether the mother studied beyond the minimum schooling age, whether the father studied beyond the minimum schooling age, father's occupation and mother's employment status, all observed when the child is age 11. We also include an indicator for financial difficulties during childhood. The variable takes the value one if (i) the interviewer reported that the household appeared to be experiencing poverty in 1965 or (ii) a member of the household self-reported having financial difficulties in the 12 months prior to being observed in either 1969 or 1974, and zero otherwise.[24]

We model the hourly wage and weekly hours worked for individuals that are employed at age 33 as follows: log hourly wage for individual i, denoted y_i, is modeled with a linear specification and a normally distributed disturbance:

$$y_i = X_{i,Y}\beta_Y + \sum_{s=0}^{5} \gamma_{s,Y}\mathbf{1}_i[s] + \sum_{j=1}^{3} \alpha_{j,Y} f_{ij} + \varepsilon_{i,Y}. \tag{6}$$

Here, $X_{i,Y}$ is a vector of observables that include partnership, fertility, months of experience, occupation and an indicator for financial difficulties during childhood. The log weekly working hours are modeled in a similar fashion as:

$$h_i = X_{i,H}\beta_H + \sum_{s=0}^{5} \gamma_{s,H}\mathbf{1}_i[s] + \sum_{j=1}^{3} \alpha_{j,H} f_{ij} + \varepsilon_{i,H}. \tag{7}$$

where β_H captures how partnership, fertility, experience and occupation (included in the vector of observables $X_{i,H}$) affect the number of hours worked in a usual week. In addition, both of the above equations include dummies of schooling levels, $\mathbf{1}_i[s]$, and the latent skills, f_{ij}.

We summarize the parameters to be estimated by a vector denoted Φ:

$$\Phi = (\beta, \gamma, \alpha, \Xi) \tag{8}$$

where β denotes the set of coefficients of the vectors of observables absent the schooling level in equations (5)-(7), γ is the set of coefficients governing the returns to schooling, α is the set of coefficients governing the returns to latent skills and Ξ are coefficients of the measurement system described in equations (3) and (4).

[24] Including this variable does not affect main results. However, it is included as an additional control in our main analysis since we use it to explore differences in the returns to externalizing behavior by childhood socioeconomic status in Section 4.5.

3.2 Estimation Procedure

We estimate the model by simulated maximum likelihood. There are three main steps in the estimation procedure. First, at each suggestion for parameter values, indexed by g and denoted $\Phi^{(g)}$, and for each individual i, we simulate a vector of unobserved skills K times and compute, for each draw of the skills, the probability of observing each schooling level, log weekly hours worked and log hourly wage. More specifically, given a parameter suggestion, we draw a block matrix of size $K \times I \times J$ from a standard normal distribution, where J is the number of latent skills, i.e. 3, and I is the number of individuals. Then, for each individual i and draw k, we construct a vector of latent skills $(f_{i1k}^{(g)}, f_{i2k}^{(g)}, f_{i3k}^{(g)})$. We compute the density functions corresponding to each outcome: the probability of individual i reaching a schooling level s ($\mathrm{P}_{ik}^{(g)}(s)$), the probability of observing wage y_i ($f_{ik}^{Y,(g)}(y_i)$) and hours worked h_i ($f_{ik}^{H,(g)}(h_i)$), for individual i, draw k and parameter suggestion (g). We also compute $f_{ik}^{M,(g)}(m_i)$, the probability of observing the classroom misbehavior measurements, for individual i, draw k and parameter suggestion (g).

Second, we compute each individual's average likelihood contribution, where the average is taken over the K draws:

$$\begin{aligned} L_i^{(g)} &= \tfrac{1}{K} \textstyle\sum_{k=1}^{K} f_{ik}^{M,(g)}(m_i) \times \prod_{s=0}^{5} \mathrm{P}_{ik}^{(g)}(s)^{\mathbf{1}[s=s_i]} \\ &\times \; f_{ik}^{H,(g)}(h_i)^{\mathbf{1}(e_i=1)} \times f_{ik}^{Y,(g)}(y_i)^{\mathbf{1}(e_i=1)} \end{aligned} \tag{9}$$

where s_i represents the observed schooling choice and e_i the observed employment status (with employed taking the value 1) in the data.

Third, we take the log of the individual likelihood contribution and sum over all individuals to form the simulated log likelihood function:

$$l^{(g)} = \sum_{i=1}^{I} \log\left(L_i^{(g)}\right) \tag{10}$$

Using both simplex and gradient methods, we evaluate $l^{(g)}$ at different values in the parameter space, indexing these suggestions by (g), and continue until a maximum is found. We implement this model for males and females separately.

4 Results

In this section, we present our main findings. We begin by presenting estimates of the econometric model outlined in Section 3. In particular, we first discuss estimates of the measurement system mapping unobserved factors to observed BSAG maladjustment syndromes (Section 4.1). Next, we discuss key findings, including the externalizing schooling penalty (Section 4.2) and the externalizing earnings premium (Section 4.3). Thereafter, we assess whether our findings on the mixed effects of externalizing behavior are the result of selection into employment, occupation or fertility (Section 4.4). Although we do find that externalizing behavior affects these outcomes, accounting for these relationships does not undermine our main findings that externalizing has positive returns in the labor market. Last, we present results showing that the benefits to externalizing do not extend to children who experienced poverty during childhood, even when we control for a additional variables such as police involvement (Section 4.5).

4.1 Mapping Unobserved Factors to Observed Misbehaviors

Starting with joint distribution of latent factors, we find a negative correlation between externalizing behavior and cognition and a positive correlation between externalizing and internalizing behavior for both males and females (Table 6). The negative relationship between the two non-cognitive skills and cognition could reflect the distribution of skill endowments at birth. It could also reflect early childhood investments if the same environments that promote externalizing and internalizing behaviors also slow cognitive development (Heckman and Cunha, 2007). An example would be childhood poverty. The positive relationship between externalizing and internalizing behavior is well-documented in the child development literature. Children under stress as a result of poverty or a family disruption, for example, tend to develop both aggressive and depressive symptoms (Wolfson, Fields, and Rose, 1987). Accounting for correlation across factors means that we avoid mis-attributing returns to skills. For example, failing to account for the positive association between externalizing and internalizing behavior could lead us to over-estimate the degree to which each non-cognitive skills negatively affect schooling.

In Table 7, we report the estimates of factor loadings mapping latent skills to BSAG maladjustment syndrome scores. Larger loadings signal a stronger relationship between the latent factor and the observed measure. Recall, we estimate the measurement system for males and for females separately. The goal is to address the possibility that estimated gender differences in returns to non-cognitive skills in school or on the labor market reflect instability of the measurement system across genders. According to Table 7, instability is not a very important concern since the estimated factor loadings are very similar for males and females. However, we find considerable variation across measurements. For both genders, the main variable identifying externalizing behavior is “hostility towards children” and the main variable identifying internalizing behavior is "unforthcomingness". In contrast, "writing off of adults and adult standards", for example, is relatively unimportant for both non-cognitive skills.

Using estimates of the distributions of underlying factors, we next plot the gender-specific distributions of each latent skill in Figure 3. We find little evidence of gender differences in the distribution of internalizing behavior or cognition. For externalizing behavior the mean and variance are higher for males. Our findings are consistent with earlier literature studying gender differences in misbehavior. However, since earlier literature has taken for granted that externalizing is broadly unproductive, the rightward-shifted externalizing distribution for boys has been viewed as a cause for concern (Bertrand and Pan, 2013).[25]

4.2 The Externalizing Penalty in School

In this section, we investigate cognitive and non-cognitive skills and educational attainment. Estimates of the ordered probit model are reported in Table 8. We find a negative association between externalizing behavior and schooling for both males and females and the point estimates are of a similar magnitude compared to findings in our crude model. The effect of family characteristics is also consistent with our initial expectations. Having parents with more education and who work in more lucrative occupational categories is related to higher educational attainment of the child. Moreover, individuals living in poverty during their childhood, a measure of family resources, are less likely to reach higher levels of education.

A difference from the crude model estimates is that the negative relationship between externalizing and schooling for females is smaller and no longer significant at conventional levels. In other words, high-externalizing females are better able to finish school in comparison to high-externalizing males. This finding may reflect how teachers are more likely to punish or refer a male versus a female child for special help for the same level of aggressive behavior (Gregory, 1977). On the other hand, we find that internalizing behavior is negatively associated with educational attainment for females, but not for males, for whom the coefficient is both small and insignificant. This is also on par with research that finds stronger effects of conduct disorders and weaker effects of anxiety and depressive symptoms for the educational attainment of males in comparison to females (Kessler et al., 1995). Finally, it is worth mentioning that even the largest coefficients on non-cognitive skills in the schooling

[25]The difference in the distribution of externalizing behavior between males and females coupled with positive returns to externalizing in the labor market raises the possibility that differences in externalizing behavior could explain the gender earnings gap. In results available upon request, we show that this is not the case. The gender earnings gap closes only slightly if we assign females the same distribution of externalizing behavior as males.

equations are between one-fifth and one-tenth the size of coefficients mapping cognition to educational attainment, which predicts schooling at similar magnitudes across genders.

In general, estimates for the schooling model are broadly consistent with literature that studies the impact of emotional problems in school. For example, McLeod and Kaiser (2004) argue that children with internalizing and externalizing problems withdraw from social relationships in school, including those with teachers, in order to minimize their exposure to negative interactions. Moreover, one of the key pathways relating behavioral problems to low educational attainment is through early educational failures such as repeating a grade or falling behind in class. If externalizing or internalizing behavior make learning more difficult, this would explain the strong negative correlation between the two non-cognitive skills and cognition (which is identified from test scores) reported in Table 6.

4.3 The Externalizing Premium on the Labor Market

Literature studying the consequences of externalizing behavior has generally limited attention to educational attainment. In contrast, we assess the relationship between childhood misbehavior and labor market outcomes. Estimates of hours and wage equations conditional on employment are in Tables 9 and 10.[26] For males, a one-standard-deviation rise in externalizing behavior predicts a 2.5% rise in hourly wages, but is not significantly related to weekly hours worked. For females, a one-standard-deviation rise in externalizing predicts a 2.5% rise in hourly wage. In addition, it is associated with a 6.9% increase in hours worked per week. The positive wage returns demonstrate that externalizing behavior is productive in the labor market even though it is counter-productive productive in school, which is a novel finding in the literature on the economic consequences of childhood misbehavior.

In contrast, internalizing behavior is negatively related to both productivity in the labor market and hours worked. For males, a one-standard-deviation rise in internalizing predicts a 4% decrease in hourly wage. We also find that cognition increases hourly wages, but does not influence the hours decision. The remaining parameters follow conventional wisdom. For example, higher educational attainment increases worker productivity, but has little effect on the number of hours worked for those already employed. Also, individuals living in or around London and who work in more skilled occupations receive higher hourly wages. Finally, males in higher-skilled occupations do not necessarily work more hours but females do.

One possible explanation of the externalizing premium is that externalizing behavior is highly negatively correlated with agreeableness (Ehrler, Evans, and McGhee, 1999). Agree-

[26]Selection into employment is discussed in the following section.

ableness is one of the "Big-5" personality traits and it predicts lower earnings (Judge, Livingston, and Hurst, 2012). To explain why, Barry and Friedman (1998) show that individuals with higher levels of agreeableness are worse negotiators as they are susceptible to being anchored by early offers in the negotiation process. Relatedly, Spurk and Abele (2011) show that less agreeable individuals are more competitive in the workplace and place a higher emphasis on career advancement. They also find that agreeableness is negatively related to work hours, which is consistent with the positive relationship between externalizing behavior and hours worked for the females in our sample. In summary, high-externalizing individuals may earn more for the same reasons that agreeable people earn less. Our findings on externalizing differ from those on agreeableness, however, since agreeableness is generally measured during adulthood and, in contrast, we measure externalizing behavior among schoolchildren. We can therefore demonstrate that externalizing behavior, though productive on the labor market, is also counterproductive in school.

Linking childhood misbehavior to earnings connects our findings to a well-developed literature linking childhood characteristics and behaviors to long-term economic outcomes. An implication of this literature is that human capital investments during childhood can have large payoffs in adulthood (Heckman and Masterov, 2007; Doyle et al., 2009; Cunha, Heckman, and Schennach, 2010). For example, Currie (2001, 2009) show that early childhood health disparities can affect future labor market outcomes through a variety of mechanisms, including performance at school. This suggests that interventions that decrease health disparities can improve the labor market performance of children born into poverty. Researchers have also linked childhood misbehavior to labor market outcomes, typically seeing misbehavior as unproductive. Our departure from the typical view suggests the need for caution in implementing policies that affect childhood non-cognitive skills. The concern is not a hypothetical one as many school systems are poised to enact policies that would evaluate children on character skills (West et al., 2015). In response to such proposals, Duckworth and Yeager (2015) emphasize concerns related to measurement, arguing that assessments of non-cognitive skills could be misleading and are subject to strategic manipulation or outright cheating.[27] These concerns are certainly valid, but our findings on mixed effects of externalizing behavior raise additional serious doubts about the utility of uniformly penalizing or rewarding schools for the development of students' non-cognitive skills. The reason is that such policies could stifle productive skills.

Even if externalizing behavior is valuable in the labor market, it is not clear if it is a skill that should be promoted. That type of policy could have its own unintended consequences, including negative externalities in the classroom if externalizing children are disruptive and

[27] See also Ivcevic and Brackett (2014) on issues with the measurement of grit.

limit other students' learning (Henneberger, Coffman, and Gest, 2016). An alternative to penalizing or attempting to eliminate externalizing behavior, however, would be to attenuate the externalizing penalty at school. Such alternatives could increase schooling without stifling valuable labor market skills. In making this distinction between policies, we draw on pedagogical research that discusses "control-oriented" teaching methods, which are designed to reduce externalizing behavior versus "relationship-oriented" methods, which are designed to strengthen the learning environment for externalizing children.[28] A simple example illustrates the difference in the two approaches. Young students who often initiate conversations with teachers at inopportune times could be punished for interrupting a lesson. Instead, they could be given a "raincheck" and invited to initiate a discussion at an appropriate time. The effectiveness of such practices is demonstrated by a randomized controlled trial of the My Teaching Partner-Secondary program (MTP-S), in which a web-mediated program on improving teacher-student in-class interaction has produced reliable gains in student achievement (Allen et al. (2011)).

4.4 Externalizing and Selection

In this section, we conduct a series of sensitivity analyses to explore whether wage returns to externalizing are explained by selection. We begin with selection into employment. Next, we study how the relationship between externalizing and earnings changes when we control for various lifecycle outcomes, including education, fertility, partnership, experience by age 33 and occupation decisions. In general, we find evidence that externalizing behavior is strongly related to a host of lifecycle outcomes. However, accounting for these relationships does not undermine the idea that externalizing is rewarded in the labor market.

4.4.1 Externalizing and Employment

Recall that wage and hours regressions are estimated on individuals who are employed. One possible concern is that the estimated relationship between externalizing and earnings is driven solely by selection into employment. In order to consider this relationship we first estimate a multinomial logit model of selection into self and paid employment while keeping the factor analysis structure constant.[29] The results can be found in Table 11 where unemployed individuals are the base group. We find important gender differences in

[28] For an overview of pedagogical techniques that foster a caring and positive student-teacher relationship, in particular, in dealing with student misbehavior, see Hamre and Pianta (2006).

[29] In other words, we keep the measurement system mapping latent skills to observed measurements of misbehavior constant so that changes in the parameters are solely attributable to changes in the control variables and not in the measurement system.

results. Females with higher levels of externalizing behavior are less likely to be unemployed and are more likely to be self-employed at age 33. For males, externalizing behavior is weakly negatively related to the employment decision. Moreover, women with high levels of internalizing behavior are significantly more likely to be unemployed, but for men it is not important. Cognition is unrelated to selection into employment since it likely works through schooling. Educational attainment seems to dominate the employment decision.

The results for externalizing behavior and females are especially concerning since they raise the possibility that high-externalizing women who are relatively productive (or who work more hours when employed) tend to self-select into employment. This could be the case if high-externalizing individuals face a lower disutility of working and are therefore observed in unemployment only if they are particularly unproductive due to other (omitted) factors. To address this concern, we exploit earnings data for individuals who were not employed at age 33, but reported earnings in a previous employment. The idea is that labor market outcomes at other periods would provide some insight into how much unemployed individuals would have earned if they had worked at age 33 (Neal and Johnson, 1996). Using this approach, the proportion of individuals in our sample for whom we obtain a measure of earnings rises from 62% to 92% (90% for males and 93.5% for females).[30] If results are driven by highly productive, high-externalizing individuals entering employment, we would expect the estimated relationship between externalizing and earnings to fall once we include earnings information on unemployed individuals.

We re-estimate the model outlined in Section 3 using the larger sample that includes individuals with earnings information from other years. Estimates are presented in Table 12. In Column [1] we present the estimated parameters using the original measure of labor market earnings. In Column [2] we use the new measure of earnings that include individuals not working at age 33. We do not find a decrease in the estimated relationship between externalizing behavior and weekly earnings once we include earnings for unemployed males. These results provide evidence against the possibility that selection into employment explains the estimated results for the males in our sample. However, as can be seen in Column [4], we do see a decrease of about 20% in the estimated relationship for females. Therefore, our estimates reflect, in part, how high-externalizing females who are high earners for unobserved reasons select into employment. However, the bottom line is that, even after we account for this decrease, the resulting relationship between externalizing behavior and earnings remains large and significant.[31]

[30] This percentage is somewhat lower for males because a higher percentage of males are always classified as self-employed.

[31] As an additional robustness check, we also experimented with a formal Heckman selection model for

4.4.2 Externalizing and other Lifecycle Outcomes

Next, we assess how estimated coefficients change when we vary the set of controls used to explain weekly hours and wages.[32] We consider four sets of controls (measured at age 33), which are added to the earnings equations successively. They are (i) dummies for educational attainment; (ii) number of children and a partnership indicator; (iii) months of experience; and (iv) occupation dummies. Estimation occurs for males and females separately and results are presented in Table 13 for males and in Table 14 for females. In Figure 4, we illustrate the changes in the estimated coefficients on externalizing as the additional controls are added. In particular, for each set of controls in the wage and hour equations, we simulate weekly earnings as we vary the externalizing factor from the lowest 5th percentile to the highest 95th percentile, keeping other latent skills and covariates at the population median.

To begin, we consider the relationship between externalizing behavior and earnings before we control for any additional outcomes. Estimates can be found in column [1] of Tables 13 and 14. Even before we control for any additional outcomes the relationship is positive for both males and females (though it is insignificant for females). This reflects results from the crude model showing that the externalizing behavior leads to a net benefit in terms of earnings, i.e., that the premium does not emerge only after we have controlled for the negative impact on schooling. In Column [2], we add schooling dummy variables and re-estimate the model. The estimated relationship between externalizing and earnings increases by around 15%. This is not surprising given the externalizing penalty in school. In other words, the relationship between externalizing behavior and earnings is stronger once we control for schooling, which is negatively associated with externalizing.

Next, we control for number of children and whether the individual has a partner (Columns [3] and [4] of Tables 13 and 14, for males and females, respectively). For males, including these additional controls does not change the estimated coefficient on externalizing. In contrast, for females, controlling for fertility doubles the magnitude of the coefficient. This gender difference is also clear in Figure 4. In Panel (b) for females, the slope of the curve, which represents how externalizing is associated with earnings, increases noticeably once we add the number of children by age 33 as a control. To understand the gender difference in how fertility affects the externalizing earnings premium, we estimate a linear regression

hourly wages using partnership and number of children as exclusion restrictions. We do not present these results since the results suggest a similar story to the one presented in Table 12 and because the exclusion restrictions are difficult to defend.

[32] For this exercise, we keep the measurement system mapping latent skills to observed measurements of misbehavior constant so that changes in the parameters are solely attributable to changes in the control variables and not in the measurement system. We also re-estimated the model allowing the factor structure to change at each different version of the model. Results do not change in any apparent way.

of the number of children by age 33 on the three factors using the previously estimated measurement system. Estimates are found in Table 15. Externalizing males and females are both likely to have a larger number of children by age 33, but based on the earnings equations (Tables 13-14), having more children is somewhat irrelevant to earnings for males, but is associated with a large drop in earnings for females.

Finally, we add months of experience and occupational choice as controls (Columns [5] and [6]). However, adding these to the model does not appreciably alter the estimated relationship between externalizing and earnings. In fact, there is little evidence that externalizing behavior drives individuals into any specific occupation once we have controlled for education. These results are found on Table 16 where we estimate a multinomial logit model of occupational sorting with unskilled occupations as the basis group. As can be seen in Table 16, externalizing is not strongly related to the occupation decision. high-externalizing males are more likely to self-select into skilled manual occupations but the parameter is only marginally significant.[33]

In summary, though externalizing behavior is related to a host of economic outcomes that also predict earnings, we have demonstrated here that the externalizing premium on the labor market is not driven by differential sorting by externalizing behavior into these outcomes. Return to Figure 4, which plots wages for different levels of externalizing using coefficients estimated assuming varying sets of controls. Though the slope does change, especially for females, depending on which controls are included, the externalizing wage premium is robust across specifications.

4.5 Childhood Poverty, Misbehavior and Earnings

Studying a sample of disadvantaged black children in the U.S., Heckman, Pinto, and Savelyev (2013) find that the an early childhood education program increased earnings in part by reducing externalizing behavior. In contrast, we show that externalizing can be valuable in the labor market. In this section, we explore whether differences in findings are explained by differences in the socioeconomic status of the group being analyzed. One possibility is that children born into poorer families face a higher likelihood of criminality or police involvement for the same level of externalizing behavior.

We estimate a version of our econometric model with two changes. First, we include a measure of police involvement at age 16 as an additional outcome equation and as an additional explanatory variable in the schooling, wage and hours equations. Second, we

[33] In additional analyses that are available upon request, we also show that the returns to externalizing do not differ significantly across occupations.

estimate the model on a sub-sample of our analytic sample, which is selected to resemble the family characteristics of the sample studied in Heckman, Pinto, and Savelyev (2013). In particular, we construct a subsample of our analytic sample consisting of subjects who faced financial difficulties during childhood. Recall, this occurs if the interviewer reported that the household appeared to be experiencing poverty in 1965 or if a member of the household self-reported having financial difficulties in the 12 months prior to being observed in either 1969 or 1974.[34] We estimate the econometric model separately for the low-SES subsample and for all other subjects in our analytic sample, which we call the high-SES subsample.[35]

Summary statistics for the low-SES sub-sample are found in Table 17. Looking at the table, the low-SES sample completes less education and earns lower wages, though hours are similar across groups. They are somewhat less likely to be employed or report having a partner, but have more children, on average. To account for potential instability of the measurement system (the mapping from underlying factors to observed variables), we estimate the measurement system for each group separately. Estimates by SES group for schooling, hours, wages and police involvement are found in Tables 18-21.

Estimating separate models by childhood SES, we find that many patterns are similar to the main model. However, we also find some important differences by childhood SES. First, we estimate a larger penalty for externalizing behavior for educational attainment among individuals that grew up in low-SES households (-0.108 versus -0.061). This finding is broadly consistent with results in Ramey (2014), who shows that externalizing blacks in the U.S. face a higher likelihood of punishment by suspension in comparison to similarly externalizing whites. This could be because schools that serve low-SES children in the UK (or black children in the U.S.) have fewer resources to address externalizing behavior and therefore react to it through suspensions or expulsions.[36]

Perhaps most importantly, we find that the labor market returns to externalizing behavior fail to extend to the low-SES subsample. For this group, the point estimate of the coefficient on externalizing behavior is zero in the wage equation. In the hours equation, the coefficient is 0.23 and insignificant for the low-SES group (versus 0.43 and significant at the 1-percent level for the high-SES group). Wage returns to the other skills are similar across the two

[34] An alternative would be to use family income. However, perhaps surprisingly, the NCDS does not collect information on family income or parental pay in the first three surveys. In the fourth survey, when children were 16 years old, categorical information was collected on each parent's work pay. However, this information on parental pay is missing for over 20% of our sample. Therefore, we decided to use the available information about financial difficulties instead.

[35] In a separate analysis, not presented here, we separated our sample into four groups by gender and socioeconomic status. Main patterns remain largely similar. However, the standard errors for the low-SES groups, when divided by gender, were too large for any useful inference to be made.

[36] There are also some differences in the returns to family characteristics, such as the father's occupation.

groups, as are the returns to education, experience and occupation. On the other hand, there are some differences in the influence of internalizing behavior and cognition for the hours worked decision. Internalizing behavior decreases hours worked for the high-SES group but not for the low-SES group and cognition increases hours worked for the low-SES group only. Other coefficients are mostly similar. However, one important caveat to the results presented in this section is that we cannot statistically differentiate the returns to externalizing behavior for the two socioeconomic groups because the standard errors in the estimates for the financially difficulties group are too large.[37]

Following the results in Heckman, Pinto, and Savelyev (2013), one explanation for possible differences in results by childhood SES status is that low-SES individuals are at a higher risk of criminal behavior for a given level of externalizing behavior. In line with this possibility, we find a strong relationship between externalizing behavior and police involvement (see Table 21). In general, our estimates suggest that low-SES individuals are more likely to have some police involvement (the estimated constant in the police involvement equation is -1.00 for the high-SES group and -0.41 for the low-SES group). However, the relationship between externalizing behavior and police involvement is stronger for the high-SES group.[38] Interestingly, we do not find much evidence that police involvement is related to worse labor market outcomes for either SES subgroup. Therefore, even though externalizing behavior predicts higher police involvement, police involvement does not appear to derail labor market prospects in the British sample we study. It is possible that the returns to externalizing behavior might be negative in a context where police involvement is highly penalized in the labor market. This is the sort of context studied in Heckman, Pinto, and Savelyev (2013), who examine a sample composed mostly of at-risk black youths in the U.S. However, for our sample, police involvement cannot explain why low-SES individuals in the British sample we study receive little payoff to externalizing behavior.

Therefore, despite our initial results showing that externalizing behavior is associated with better labor market outcomes, this positive association does not extend to individuals who faced poverty during childhood. In other words, the payoffs to non-cognitive skills are context-dependent, as argued in Lundberg (2013). To explain differences in returns to skills across socioeconomic groups, we are therefore left with several distinct, but related possibilities. The first is that there are true differences in productivity of externalizing behavior across groups. This is possible if, for example, children born into wealthier families are bet-

[37] One possibility is that differences in returns are due to instability of the measurement system across groups. However, we estimated the measurement system separately for each group and find that the factor loadings are remarkably similar for the high-SES and low-SES group (Table S4).

[38] Interestingly, internalizing behavior and cognition are associated with less police involvement, though the coefficients are much larger in magnitude for high-SES individuals.

ter able to channel aggressive tendencies into productive activities.[39] A second possibility is that high-externalizing individuals from lower classes face different selection rules than their higher-SES counterparts, but which are not observed by the econometrician. For example, managers or co-workers may view high-externalizing individuals from high-SES families as ambitious leaders and be willing to hire them in high-wage positions or to promote them. In contrast, high-externalizing individuals from lower SES families may find their advancement thwarted if they are viewed as disruptive, aggressive or impolite. If so, high-externalizing individuals from low-SES families are not unproductive *per se*, but instead sort into jobs where they earn less. In both cases, childhood SES and externalizing exhibit complementarities and children from poorer families are unable to unleash the potential of an otherwise lucrative skill.

5 Conclusion

Few would argue that stronger cognition or grit would improve outcomes on almost any conceivable economic dimension. In this paper, we illustrate that it is generally not meaningful to think of non-cognitive skill as either good or bad *per se*. We have demonstrated that the same non-cognitive skill can be productive in one context and counterproductive in another. Our findings suggest that investments in human capital should be evaluated in light of this possibility. In particular, mixed effects of externalizing behavior suggest caution in devising policies that target children with apparently undesirable behaviors. Such policies may pay off in the short-run by improving educational outcomes, but may also be costly in the long-run by stifling a productive labor market skill. We also show important differences across socioeconomic groups in the returns to skills. This further complicates policies centering around non-cognitive skill formation, suggesting that individuals from disadvantaged backgrounds may suffer from an inability to profit from productive skills. Our results are salient given recent efforts to include measures of non-cognitive skills as part of schools' and teachers' performance ratings.

One direction for future research would be to better understand the heterogeneity of effects of non-cognitive skills across groups. For example, Ramey (2014) shows that high-externalizing blacks are more likely to be suspended from school than equally externalizing whites. This result could explain possible differences in the returns of externalizing behavior since, for both groups, suspensions are associated with low schooling attainment and lower earnings. Extending this type of research to consider labor market outcomes could help

[39] See, for example, Doyle et al. (2009) on the timing of investments to decrease inequality.

to ascertain whether differences in returns to the same skills could help explain stubbornly persistent inequality across groups.

References

Achenbach, Thomas M., Stephanie H. McConaughy, and Catherine T. Howell. 1987. “Child/Adolescent Behavioral and Emotional Problems: Implications of Cross-Information Correlations for Situational Specificity.” *Psychological Bulletin* 101 (2):213–232.

Agan, Amanda Y. 2011. “Non-Cognitive Skills and Crime.” University of Chicago.

Aizer, Anna. 2009. “Neighborhood Violence and Urban Youth.” *The Problems of Disadvantaged Youth: An Economic Perspective* :275.

Allen, Joseph P., Robert C. Pianta, Anne Gregory, Amori Yee Mikami, and Janetta Lun. 2011. “An Interation-Based Approach to Enhancing Secondary School Instruction and Student Achievement.” *Science* 333.

Almlund, Mathilde, Angela Lee Duckworth, James Heckman, and Tim Kautz. 2011. “Personality Psychology and Economics.” *Handbook of the Economics of Education* 4 (1).

Barry, Bruce and Raymond A Friedman. 1998. “Bargainer Characteristics in Distributive and Integrative Negotiation.” *Journal of Personality and Social Psychology* 74 (2):345.

Becker, Gary Stanley. 1967. *Human Capital and the Personal Distribution of Income: An Analytical Approach.* Institute of Public Administration.

Bertrand, Marianne and Jessica Pan. 2013. “The Trouble with Boys: Social Influences and the Gender Gap in Disruptive Behavior.” *American Economic Journal: Applied Economics* 5 (1):32–64.

Blanden, Jo, Paul Gregg, and Lindsey Macmillan. 2007. “Accounting for Intergenerational Income Persistence: Noncognitive Skills, Ability and Education.” *The Economic Journal* 117 (519):C43–C60.

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

Card, David. 2012. "Earnings, Schooling, and Ability Revisited." *35th Anniversary Retrospective* 35:111.

Conti, Gabriella, Sylvia Frühwirth-Schnatter, James J Heckman, and Rémi Piatek. 2014. "Bayesian Exploratory Factor Analysis." *Journal of Econometrics* 183 (1):31–57.

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

Currie, Janet. 2001. "Early Childhood Education Programs." *The Journal of Economic Perspectives* 15 (2):213–238.

———. 2009. "Healthy, Wealthy, and Wise: Socioeconomic Status, Poor Health in Childhood, and Human Capital Development." *Journal of Economic Literature* 47 (1):87–122.

Doyle, Orla, Colm P Harmon, James J Heckman, and Richard E Tremblay. 2009. "Investing in Early Human Development: Timing and Economic Efficiency." *Economics & Human Biology* 7 (1):1–6.

Duckworth, Angela L, Christopher Peterson, Michael D Matthews, and Dennis R Kelly. 2007. "Grit: Perseverance and Passion for Long-Term Goals." *Journal of Personality and Social Psychology* 92 (6):1087.

Duckworth, Angela L and David Scott Yeager. 2015. "Measurement Matters Assessing Personal Qualities Other than Cognitive Ability for Educational Purposes." *Educational Researcher* 44 (4):237–251.

Duncan, Greg J and Rachel Dunifon. 2012. "Introduction to 'Soft-Skills' and Long-Run Labor Market Success." *Research in Labor Economics* 35:309–312.

Duncan, Greg J and Katherine Magnuson. 2011. "The Nature and Impact of Early Achievement Skills, Attention Skills, and Behavior Problems." In *Whither Opportunity? Rising Inequality, Schools, and Children's Life Chances*. Russell Sage Foundation, 47–69.

Ehrler, David J, J Gary Evans, and Ron L McGhee. 1999. "Extending Big-Five Theory into Childhood: A Preliminary Investigation into the Relationship Between Big-Five Personality Traits and Behavior Problems in Children." *Psychology in the Schools* 36 (6):451–458.

Farmer, Elizabeth MZ. 1993. "Externalizing Behavior in the Life Course The Transition From School to Work." *Journal of Emotional and Behavioral Disorders* 1 (3):179–188.

———. 1995. "Extremity of Externalizing Behavior and Young Adult Outcomes." *Journal of Child Psychology and Psychiatry* 36 (4):617–632.

Fronstin, Paul, David H Greenberg, and Philip K Robins. 2005. "The Labor Market Consequences of Childhood Maladjustment." *Social Science Quarterly* 86:1170–1195.

Ghodsian, M. 1977. "Children's Behaviour and the BSAG: Some Theoretical and Statistical Considerations." *British Journal of Social and Clinical Psychology* 16 (1):23–28.

Gregory, Mary K. 1977. "Sex Bias in School Referrals." *Journal of School Psychology* 15 (1):5–8.

Hamre, Bridget K. and Robert C. Pianta. 2006. "Student-Teacher Relationships." In *Children's Needs III: Development, Prevention and Intervention*, edited by G. Bear and Kathleen M. Minke, chap. 5. National Association of School Psychologists 49–60.

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

Heckman, James J and Tim Kautz. 2013. "Fostering and Measuring Skills: Interventions that Improve Character and Cognition." NBER working paper.

Heckman, James J and Dimitriy V Masterov. 2007. "The Productivity Argument for Investing in Young Children." *Applied Economic Perspectives and Policy* 29 (3):446–493.

Heckman, James J, Rodrigo Pinto, and Peter Savelyev. 2013. "Understanding the Mechanisms through Which an Influential Early Childhood Program Boosted Adult Outcomes." *American Economic Review* 103 (6):2052–86.

Heckman, James J and Yona Rubinstein. 2001. "The Importance of Noncognitive Skills: Lessons from the GED Testing Program." *The American Economic Review* 91 (2):145–149.

Henneberger, Angela K, Donna L Coffman, and Scott D Gest. 2016. "The Effect of Having Aggressive Friends on Aggressive Behavior in Childhood: Using Propensity Scores to Strengthen Causal Inference." *Social Development* .

Ivcevic, Zorana and Marc Brackett. 2014. "Predicting School Success: Comparing Conscientiousness, Grit, and Emotion Regulation Ability." *Journal of Research in Personality* 52:29–36.

Jackson, Michelle. 2006. "Personality Traits and Occupational Attainment." *European Sociological Review* 22 (2):187–199.

Judge, Timothy A, Beth A Livingston, and Charlice Hurst. 2012. "Do Nice Guys and Gals Really Finish Last? The Joint Effects of Sex and Agreeableness on Income." *Journal of Personality and Social Psychology* 102 (2):390.

Kessler, Ronald C, Cindy L Foster, William B Saunders, and Paul E Stang. 1995. "Social Consequences of Psychiatric Disorders, I: Educational Attainment." *American Journal of Psychiatry* 152 (7):1026–1032.

Lundberg, Shelly. 2013. "The College Type: Personality and Educational Inequality." *Journal of Labor Economics* 31 (3):421–441.

McLeod, Jane D and Karen Kaiser. 2004. "Childhood Emotional and Behavioral Problems and Educational Attainment." *American Sociological Review* 69 (5):636–658.

Neal, Derek A and William R Johnson. 1996. "The Role of Premarket Factors in Black-White Wage Differences." *Journal of Political Economy* 104 (5):869–895.

Ramey, David M. 2014. *The Social Control of Childhood Behavior via Criminalization or Medicalization: Why Race Matters*. Ph.D. thesis, The Ohio State University.

Rao, Calyampudi Radhakrishna and Sandip Sinharay. 2006. *Handbook of statistics: Psychometrics*, vol. 26. Elsevier.

Roy, Andrew Donald. 1951. "Some Thoughts on the Distribution of Earnings." *Oxford Economic Papers* 3 (2):135–146.

Sciulli, Dario. 2016. "Adult Employment Probabilities of Socially Maladjusted Children." *Journal of Behavioral and Experimental Economics* 60:9–22.

Segal, Carmit. 2013. "Misbehavior, Education, and Labor Market Outcomes." *Journal of the European Economic Association* 11 (4):743–779.

Shepherd, Peter. 2013. "Bristol Social Adjustment Guides at 7 and 11 years." Centre for Longitudinal Studies.

Spurk, Daniel and Andrea E Abele. 2011. "Who Earns More and Why? A Multiple Mediation Model From Personality to Salary." *Journal of Business and Psychology* 26 (1):87–103.

Stott, Denis Herbert, Emily G Sykes, and NC Marston. 1974. *The Social Adjustment of Children: Manual to the Bristol Social Adjustment Guides*. Hodder & Stoughton.

West, Martin R, Matthew A Kraft, Amy S Finn, Rebecca E Martin, Angela L Duckworth, Christopher FO Gabrieli, and John DE Gabrieli. 2015. "Promise and Paradox Measuring Students Non-Cognitive Skills and the Impact of Schooling." *Educational Evaluation and Policy Analysis* .

Willis, Robert J. and Sherwin Rosen. 1979. "Education and Self-Selection." *Journal of Political Economy* 87 (5):S7–S36.

Wolfson, Johanna, Joel H Fields, and Susan A Rose. 1987. "Symptoms, Temperament, Resiliency, and Control in Anxiety-Disordered Preschool Children." *Journal of the American Academy of Child & Adolescent Psychiatry* 26 (1):16–22.

Yeung, W Jean, Miriam R Linver, and Jeanne Brooks-Gunn. 2002. "How Money Matters for Young Children's Development: Parental Investment and Family Processes." *Child Development* :1861–1879.

6 Tables and Figures

Table 1: LATENT FACTORS AND THEIR MEASUREMENTS

Latent Skill	Measures
Externalizing Behavior	◇ Hostility Towards Adults ◇ Hostility Towards Children ◇ Anxiety for Acceptance by Adults ◇ Anxiety for Acceptance by Children ◇ Restlessness ◇ Inconsequential Behavior ◇ Writing Off of Adults and Adult Standards
Internalizing Behavior	◇ Depression ◇ Withdrawal ◇ Unforthcomingness ◇ Writing Off of Adults and Adult Standards
Cognition	◇ Reading Comprehension Test Score ◇ Mathematics Test Score ◇ Non Verbal Score on General Ability Test ◇ Verbal Score on General Ability Test

Notes: This table lists the three latent factors used in the empirical analysis (externalizing behavior, internalizing behavior and cognition) and the observed variables used to identify them. Measures for externalizing and internalizing behaviors are drawn from the BSAG maladjustment variables, derived from teachers' reports of misbehavior. For cognition, a series of aptitude test scores are used as measures. See Appendix A for further details.

Table 2: Summary Statistics

	Both	Males	Females	Diff
No Formal Education	0.112	0.102	0.121	*
	(0.315)	(0.303)	(0.326)	
CSE	0.128	0.112	0.142	***
	(0.334)	(0.316)	(0.349)	
O Level	0.347	0.307	0.386	***
	(0.476)	(0.461)	(0.487)	
A Level	0.146	0.190	0.103	***
	(0.353)	(0.393)	(0.305)	
Higher Education	0.146	0.150	0.142	
	(0.353)	(0.357)	(0.349)	
Higher Degree	0.121	0.138	0.105	***
	(0.326)	(0.345)	(0.307)	
Hourly Wage	6.637	7.643	5.457	***
	(3.053)	(2.967)	(2.712)	
Weekly Hours Worked	36.35	43.54	27.93	***
	(12.65)	(7.757)	(12.07)	
Weekly Earnings	252.5	329.2	162.4	***
	(152.5)	(134.5)	(119.5)	
Experience	145.9	164.0	128.2	***
	(50.92)	(45.65)	(49.56)	
In Paid Work	0.804	0.919	0.692	***
	(0.397)	(0.273)	(0.462)	
Self Employed	0.162	0.197	0.115	***
	(0.368)	(0.398)	(0.319)	
Has a Partner	0.873	0.877	0.869	
	(0.333)	(0.328)	(0.338)	
Number of Children	1.475	1.349	1.597	***
	(1.125)	(1.152)	(1.085)	
London	0.300	0.293	0.306	
	(0.458)	(0.455)	(0.461)	
Observations	7324	3612	3712	7324

Notes: Summary statistics for the analytic sample of 7,324 individuals (Column [1]) and then separately for males (Column [2]) and for females (Column [3]). For education categories, employment and partnership, entries are in the form of percentages divided by 100. Experience is measured in months and wages and weekly earnings are in 1992 British pounds. Self Employed means the percentage of individuals in paid work who are also self-employed. In Column [4], *, ** and *** mean that differences between males and females are significant at the 10, 5 and 1 percent levels, respectively.

Table 3: Summary Statistics - BSAG Variables

	Both	Males	Females	Diff
Hostility Towards Adults	0.766	0.896	0.639	***
	(1.754)	(1.866)	(1.628)	
Hostility Towards Children	0.240	0.266	0.215	**
	(0.719)	(0.777)	(0.656)	
Anxiety for Acceptance by Adults	0.515	0.481	0.548	*
	(1.154)	(1.094)	(1.210)	
Anxiety for Acceptance by Children	0.298	0.403	0.197	***
	(0.761)	(0.899)	(0.579)	
Restlessness	0.195	0.242	0.149	***
	(0.522)	(0.575)	(0.459)	
Inconsequential Behavior	1.263	1.676	0.862	***
	(1.868)	(2.153)	(1.432)	
Depression	0.933	1.086	0.784	***
	(1.452)	(1.534)	(1.350)	
Withdrawal	0.307	0.374	0.242	***
	(0.770)	(0.876)	(0.645)	
Unforthcomingness	1.479	1.538	1.421	*
	(2.036)	(2.009)	(2.060)	
Writing Off of Adults and Adult Standards	0.910	1.128	0.698	***
	(1.588)	(1.788)	(1.333)	
Observations	7324	3612	3712	7324

Notes: Summary statistics for maladjustment syndrome scores for our sample of 7324 individuals. Measures constructed using teachers' reports of misbehavior or misconduct in school. Statistics are reported separately for all individuals (Column [1]), for males (Column [2]) and for females (Column [3]). For each maladjustment syndrome, a child receives a score, which is an integer between 0 and 15, with 15 indicating a persistent display of behavior described by the maladjustment syndrome. In the table, entries are averages for each syndrome for the analytic sample. In Column [4], *, ** and *** mean that differences between males and females are significant at the 10, 5 and 1 percent levels, respectively.

Table 4: Crude Model: Educational Attainment

Variable	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Misbehavior	-.364***	-.138***	.	.	.	.	.
Externalizing	.	.	-.231***	-.092***	-.097***	-.121***	-.062**
Internalizing	.	.	-.183***	-.066***	-.060***	-.036*	-.090***
Cognition	.	.806***	.	.807***	.718***	.695***	.753***
Father Edu	.	.	.	.	.254***	.189***	.316***
Mother Edu.	.	.	.	.	.268***	.224***	.311***
No Info on Father Figure	.	.	.	.	.173**	.130	.220**
Father in Skilled Occupation	.	.	.	.	.167***	.203***	.133***
Father in Managerial Occupation	.	.	.	.	.414***	.462***	.369***
Working Mother	.	.	.	.	.019	.001	.037
Female	-.303***	-.333***	-.304***	-.334***	-.335***	.	.
Obs.	7324	7324	7324	7324	7324	3612	3712

Notes: This table contains parameter estimates from ordered probit used to link non-cognitive skills to educational attainment. We estimate the ordered probability of choosing 1 of 6 schooling levels on a set of observable variables along with proxies for unobserved skills. To construct proxies for unobserved skills, we sum up all variables used to measure that skill in subsequent analysis and then normalize each unobserved skill. Models [1]-[5] include all individuals and a gender dummy, Model [6] includes only males and Model [7] only females. * denotes the coefficient is significant at the 10% level, ** denotes the coefficient is significant at the 5% level and *** denotes the coefficient is significant at the 1% level.

Table 5: CRUDE MODEL: LOG WEEKLY EARNINGS

Variable	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Misbehavior	-.105***	-.028***	.	.	.	.	.	.
Externalizing	.	.	-.019*	.025**	.034***	.046***	.018**	.090***
Internalizing	.	.	-.101***	-.059***	-.050***	-.045***	-.045***	-.041**
Cognition	.	.205***	.	.204***	.084***	.053***	.052***	.057***
CSE	.	.	.	.	.078**	-.015	.013	-.021
O Level	.	.	.	.	.207***	.033	.070**	.0003
A Level	.	.	.	.	.343***	.116***	.096***	.132**
Higher Education	.	.	.	.	.515***	.178***	.156***	.154***
Higher Degree	.	.	.	.	.644***	.386***	.291***	.368***
Has a Partner	.	.	.	.	.	.085***	.121***	.031
Number of Children	.	.	.	.	.	-.106***	.015**	-.258***
Experience	.	.	.	.	.	.003***	.001***	.002***
Skilled Manual Occu.	.	.	.	.	.	.259***	.091***	.310***
Skilled Non-manual Occu.	.	.	.	.	.	.241***	.172***	.301***
Managerial Occupation	.	.	.	.	.	.514***	.266***	.695***
Female	-.933***	-.916***	-.932***	-.915***	-.867***	-.739***	.	.
London	.249***	.219***	.248***	.219***	.205***	.161***	.193***	.124***
Const.	5.639***	5.615***	5.639***	5.616***	5.319***	4.808***	5.026***	4.403***
Obs.	4936	4936	4936	4936	4936	4936	2664	2272

Notes: This table contains parameter estimates from OLS regressions used to link non-cognitive skills to earnings. We regress log earnings of workers on a set of observable variables along with proxies for unobserved skills. To construct proxies for unobserved skills, we sum up all variables used to measure that skill in subsequent analysis and then normalize each unobserved skill. Models [1]-[6] include all individuals and a gender dummy, Model [7] includes only males and Model [8] only females. * denotes the coefficient is significant at the 10% level, ** denotes the coefficient is significant at the 5% level and *** denotes the coefficient is significant at the 1% level.

Table 6: Measurement Error Model: Latent Factor Correlation Matrix

	Males		
	Externalizing	Internalizing	Cognition
Externalizing	1.000	0.575	-0.380
Internalizing	0.575	1.000	-0.358
Cognition	-0.380	-0.358	1.000
	Females		
	Externalizing	Internalizing	Cognition
Externalizing	1.000	0.593	-0.400
Internalizing	0.593	1.000	-0.398
Cognition	-0.400	-0.398	1.000

Notes: This table lists the correlation matrix of the three latent skills by gender.

Table 7: Measurement Error Model: Factor Loadings

Latent Skill	Measures	Males	Females
Externalizing Behavior	Inconsequential Behavior	1.000	1.000
	Hostility Towards Adults	1.680	1.312
	Hostility Towards Children	2.387	1.632
	Anxiety for Acceptance by Adults	1.204	0.763
	Anxiety for Acceptance by Children	1.699	1.522
	Restlessness	1.784	1.572
	Writing Off of Adults and Adult Standards	0.397	0.299
Internalizing Behavior	Withdrawal	1.000	1.000
	Depression	0.932	1.137
	Unforthcomingness	1.711	1.878
	Writing Off of Adults and Adult Standards	0.605	0.847
Cognition	Verbal Score on General Ability Test	1.000	1.000
	Reading Comprehension Test Score	0.596	0.579
	Mathematics Test Score	1.086	1.065
	Non Verbal Score on General Ability Test	0.733	0.766

Notes: This table lists the factor loadings that express the relationship between each observed measure and the underlying factor it identifies.

Table 8: ME Model: Ordered Probit for Educational Attainment

	[M]	[F]
Externalizing Factor	-0.119***	-0.046
Internalizing Factor	-0.019	-0.064**
Cognition	0.702***	0.725***
Mother Education	0.189***	0.327***
Father Education	0.250***	0.329***
No Father Info.	0.200*	0.271**
Father in Skilled Occupation	0.174***	0.113**
Father in Managerial Occupation	0.442***	0.331***
Working Mother	0.019	0.039
In Financial Difficulties	-0.311***	-0.303***

Notes: This table contains parameter estimates from an Ordered Probit model used to link non-cognitive skills to educational attainment. We estimate educational attainment on a set of observable variables along with the unobserved factors. The coefficients on the three factors have been standardized to represent a 1 standard deviation effect. * denotes the coefficient is significant at the 10% level, ** denotes the coefficient is significant at the 5% level and *** denotes the coefficient is significant at the 1% level.

Table 9: ME Model: Log Hourly Wages

	[M]	[F]
Externalizing Factor	0.025**	0.025**
Internalizing Factor	-0.040***	-0.021*
Cognition	0.053***	0.048***
CSE	0.003	-0.001
O-Level	0.083***	0.035
A-Level	0.118***	0.122***
Higher Education	0.184***	0.257***
Higher Degree	0.333***	0.409***
Partner Dummy	0.109***	0.064***
Number of Children	0.011*	-0.067***
Experience	0.001***	0.001***
Skilled Manual Occu.	0.070***	0.070**
Skilled Non-manual Occu.	0.199***	0.173***
Managerial Occu.	0.255***	0.374***
London Dummy	0.180***	0.123***
In Financial Difficulties	-0.026	-0.014
Constant	1.334***	1.179***

Notes: This table contains parameter estimates from OLS regressions used to link non-cognitive skills to hourly wages. We regress log hourly wages on a set of observable variables along with the unobserved factors. The coefficients on the three factors have been standardized to represent a 1 standard deviation effect. * denotes the coefficient is significant at the 10% level, ** denotes the coefficient is significant at the 5% level and *** denotes the coefficient is significant at the 1% level.

Table 10: ME Model: Log Weekly Hours Worked

	[M]	[F]
Externalizing Factor	0.009	0.069***
Internalizing Factor	-0.016**	-0.037**
Cognition	0.000	0.018
CSE	0.007	-0.022
O-Level	-0.021	-0.040
A-Level	-0.034*	0.003
Higher Education	-0.031	-0.110***
Higher Degree	-0.051**	-0.047
Partner Dummy	0.012	-0.033
Number of Children	0.005	-0.190***
Experience	0.000	0.001***
Skilled Manual Occu.	0.023*	0.235***
Skilled Non-manual Occu.	-0.027*	0.127***
Managerial Occu.	0.011	0.317***
London Dummy	0.013	-0.000
In Financial Difficulties	-0.008	0.043*
Constant	3.748***	3.426***

Notes: This table contains parameter estimates from OLS regressions used to link non-cognitive skills to hours worked. We regress log weekly hours worked on a set of observable variables along with the unobserved factors. The coefficients on the three factors have been standardized to represent a 1 standard deviation effect. * denotes the coefficient is significant at the 10% level, ** denotes the coefficient is significant at the 5% level and *** denotes the coefficient is significant at the 1% level.

Table 11: ME Model: Employment Decision

	Males		Females	
	Self-Employed	Employee	Self-Employed	Employee
Externalizing Factor	-0.055	-0.211*	0.377***	0.144**
Internalizing Factor	-0.198	-0.074	-0.307**	-0.208***
Cognition	0.154	0.246*	0.063	-0.006
CSE	0.726***	0.740***	0.422	0.182
O-Level	0.672***	0.434**	0.355	0.240*
A-Level	1.093***	1.064***	0.431	0.022
Higher Education	0.448	0.891***	0.356	0.499***
Higher Degree	0.210	0.639*	0.271	0.281
Partner Dummy	1.545***	1.566***	0.280	0.274**
Number of Children	-0.168**	-0.255***	-0.279***	-0.549***
Father in Skilled Occupation	-0.316	-0.107	-0.195	0.277***
Father in Managerial Occupation	-0.362	0.035	-0.414*	0.201*
Working Mother	-0.091	0.145	-0.108	0.238***
In Financial Difficulties	-0.366*	-0.329**	0.005	0.303***
Constant	-0.639*	0.463	-1.012***	0.713***

Notes: This table contains parameter estimates from a multinomial logit model used to link non-cognitive skills to the employment decision. We model the the employment decision as a linear function of a set of observable variables along with the unobserved skills. The coefficients on the three factors have been standardized to represent a 1 standard deviation effect. The base category is not-employed at age 33. * denotes the coefficient is significant at the 10% level, ** denotes the coefficient is significant at the 5% level and *** denotes the coefficient is significant at the 1% level.

Table 12: ME Model: Log Weekly Earnings, Imputing Missing Earnings

	[Males]		[Females]	
	[1]	[2]	[3]	[4]
Externalizing Factor	0.039***	0.045**	0.084***	0.066***
Internalizing Factor	-0.061***	-0.054***	-0.049**	-0.041*
Cognition	0.052***	0.088***	0.062***	0.029
CSE	0.017	-0.019	-0.020	-0.065
O-Level	0.073***	0.002	0.002	0.012
A-Level	0.094***	0.062	0.135**	0.178***
Higher Education	0.158***	0.103**	0.158***	0.180***
Higher Degree	0.295***	0.277***	0.376***	0.453***
Partner Dummy	0.124***	0.151***	0.032	0.045
Number of Children	0.015**	0.001	-0.257***	-0.229***
Experience	0.001***	0.002***	0.002***	0.002***
Skilled Manual Occu.	0.089***	0.080**	0.306***	0.358***
Skilled Non-manual Occu.	0.174***	0.195***	0.301***	0.405***
Managerial Occu.	0.266***	0.339***	0.693***	0.774***
London Dummy	0.192***	0.201***	0.123***	0.166***
In Financial Difficulties	-0.033*	-0.029	0.029	-0.011
Constant	5.064***	5.019***	4.613***	4.453***
Obs	2264	3257	2272	3470

Notes: This table contains parameter estimates from a linear regression used to link non-cognitive skills to weekly earnings under alternative specifications. We regress log weekly earnings of workers on a set of observable variables along with the three factors. In Model [1], the dependent variable is reported gross weekly earnings for *males* that were working at age 33. In Model [2], we impute weekly earnings for *males* that were not working at age 33 using self-reported weekly earnings from previous jobs and include those observations in the regression. In Model [3], the dependent variable is reported gross weekly earnings for *females* that were working at age 33. In Model [4], we impute weekly earnings for *females* that were not working at age 33 using self-reported weekly earnings from previous jobs and include those observations in the regression. With the imputation, we manage to compute the earnings for 92% of the individuals in our sample. * denotes the coefficient is significant at the 10% level, ** denotes the coefficient is significant at the 5% level and *** denotes the coefficient is significant at the 1% level.

Table 13: ME Model: Log Weekly Earnings (Males), Varying Controls

	[1]	[2]	[3]	[4]	[5]	[6]
Externalizing Factor	0.036***	0.041***	0.039***	0.037***	0.038***	0.039***
Internalizing Factor	-0.079***	-0.077***	-0.073***	-0.069***	-0.068***	-0.061***
Cognition	0.138***	0.072***	0.072***	0.070***	0.073***	0.052***
CSE	.	0.051*	0.050*	0.053*	0.037	0.017
O-Level	.	0.137***	0.139***	0.129***	0.111***	0.073***
A-Level	.	0.172***	0.176***	0.169***	0.157***	0.094***
Higher Education	.	0.286***	0.289***	0.278***	0.267***	0.158***
Higher Degree	.	0.374***	0.383***	0.368***	0.415***	0.295***
Number of Children	.	.	0.029***	0.012*	0.011	0.015**
Partner Dummy	.	.		0.158***	0.147***	0.124***
Experience	.	.	.		0.001***	0.001***
Skilled Manual Occu.	.	.	.	.	.	0.089***
Skilled Non-manual Occu.	.	.	.	.	.	0.174***
Managerial Occu.	.	.	.	.	.	0.266***
London Dummy	0.215***	.0.212***	0.214***	0.215***	0.216***	0.192***
In Financial Difficulties	-0.070***	-0.043**	-0.044**	-0.043**	-0.040**	-0.033*
Constant	5.666***	5.487***	5.447***	5.336***	5.148***	5.064***

Notes: This table contains parameter estimates from OLS regressions used to link non-cognitive skills to weekly earnings with different sets of controls. We regress log weekly earnings of male workers on a set of observable variables along with the three factors. The goal is to undertand how the relationship between non-cognitive skills to earnings change as we change the set of additional regressors. * denotes the coefficient is significant at the 10% level, ** denotes the coefficient is significant at the 5% level and *** denotes the coefficient is significant at the 1% level.

Table 14: ME MODEL: LOG WEEKLY EARNINGS (FEMALES), VARYING CONTROLS

	[1]	[2]	[3]	[4]	[5]	[6]
Externalizing Factor	0.036	0.043*	0.079***	0.080***	0.086***	0.084***
Internalizing Factor	-0.046	-0.029	-0.062***	-0.060***	-0.065***	-0.049**
Cognition	0.279***	0.109***	0.089***	0.087***	0.080***	0.062***
CSE	.	0.089	0.067	0.068	0.041	-0.020
O-Level	.	0.251***	0.154***	0.154***	0.119**	0.002
A-Level	.	0.509***	0.339***	0.339***	0.329***	0.135**
Higher Education	.	0.732***	0.579***	0.579***	0.541***	0.158***
Higher Degree	.	0.961***	0.727***	0.726***	0.799***	0.376***
Number of Children	.	.	-0.323***	-0.327***	-0.285***	-0.257***
Partner Dummy	.	.	.	0.064	0.048	0.032
Experience	.	.	.	.	0.002***	0.002***
Skilled Manual Occu.	.	.	.	.	.	0.306***
Skilled Non-manual Occu.	.	.	.	.	.	0.301***
Managerial Occu.	.	.	.	.	.	0.693***
London Dummy	0.218***	0.188***	0.136***	0.135***	0.135***	0.123***
In Financial Difficulties	-0.077*	-0.026	0.024	0.026	0.035	0.029
Constant	4.996***	4.634***	5.153***	5.106***	4.744***	4.613***

Notes: This table contains parameter estimates from OLS regressions used to link non-cognitive skills to weekly earnings with different sets of controls. We regress log weekly earnings of female workers on a set of observable variables along with the three factors. The goal is to undertand how the relationship between non-cognitive skills to earnings change as we change the set of additional regressors. * denotes the coefficient is significant at the 10% level, ** denotes the coefficient is significant at the 5% level and *** denotes the coefficient is significant at the 1% level.

Table 15: ME Model: Number of Children

	[Males]	[Females]
Externalizing Factor	0.070***	0.051***
Internalizing Factor	-0.089***	-0.026
Cognition	-0.014	-0.014
CSE	-0.059	-0.005
O-Level	-0.028	-0.104***
A-Level	-0.088	-0.206***
Higher Education	-0.076	-0.231***
Higher Degree	-0.229***	-0.370***
Children in HH at 11	0.037***	0.031***
In Financial Difficulties	0.039	0.008
Constant	0.222***	0.542***

Notes: This table contains parameter estimates from a regression model used to link non-cognitive skills to the number of children. We model the number of children as a linear function of a set of observable variables along with the unobserved skills. The coefficients on the three factors have been standardized to represent a 1 standard deviation effect. * denotes the coefficient is significant at the 10% level, ** denotes the coefficient is significant at the 5% level and *** denotes the coefficient is significant at the 1% level.

Table 16: ME Model: Occupation Decision

	Males		
	Skilled Manual	Skilled Non-Manual	Managerial
Externalizing Factor	0.239*	-0.021	0.032
Internalizing Factor	-0.324**	-0.191**	-0.263***
Cognition	0.029	0.279***	0.208*
CSE	0.077	0.689***	0.805***
O-Level	0.536**	1.374***	1.526***
A-Level	1.070***	1.537***	2.470***
Higher Education	1.137***	0.840***	3.679***
Higher Degree	-0.112	1.209***	4.397***
Partner Dummy	0.129	0.487***	0.376**
Number of Children	-0.446***	-0.382***	-0.640***
Father in Skilled Occupation	-0.331	-0.220	-0.354**
Father in Managerial Occupation	-0.277	-0.413***	-0.556***
Working Mother	0.110	-0.105	0.045
In Financial Difficulties	0.243	-0.185	0.122
Constant	-0.839**	-0.169	-1.087***
	Females		
	Skilled Manual	Skilled Non-Manual	Managerial
Externalizing Factor	0.127	-0.099	-0.034
Internalizing Factor	-0.116	-0.163	-0.245**
Cognition	0.041	0.689***	0.594***
CSE	0.564***	0.992***	0.534**
O-Level	1.089***	1.630***	1.209***
A-Level	1.691***	2.350***	2.089***
Higher Education	1.228***	2.484***	2.990***
Higher Degree	0.746	2.914***	4.077***
Partner Dummy	0.459***	0.412*	0.821***
Number of Children	-0.013	-0.155**	-0.142**
Father in Skilled Occupation	0.221	-0.205	-0.583***
Father in Managerial Occupation	0.089	-0.537**	-0.979***
Working Mother	0.126	0.155	-0.058
In Financial Difficulties	-0.390***	-0.482**	-0.323**
Constant	-0.533**	-2.000***	-0.850***

Notes: This table contains parameter estimates from a multinomial logit model used to link non-cognitive skills to the occupation decision. We model the occupation decision as function of a set of observable variables along with the unobserved skills. The coefficients on the three factors have been standardized to represent a 1 standard deviation effect. The base category are unskilled occupations. * denotes the coefficient is significant at the 10% level, ** denotes the coefficient is significant at the 5% level and *** denotes the coefficient is significant at the 1% level.

Table 17: Summary Statistics, Subsamples by SES

	Both	High-SES	low-SES	Diff
No Formal Education	0.112	0.0839	0.257	***
	(0.315)	(0.277)	(0.437)	
CSE	0.128	0.116	0.191	***
	(0.334)	(0.320)	(0.393)	
O Level	0.346	0.351	0.324	
	(0.476)	(0.477)	(0.468)	
A Level	0.146	0.158	0.0871	***
	(0.354)	(0.365)	(0.282)	
Higher Education	0.146	0.156	0.0982	***
	(0.354)	(0.362)	(0.298)	
Higher Degree	0.122	0.137	0.0427	***
	(0.327)	(0.344)	(0.202)	
Hourly Wage	6.635	6.832	5.595	***
	(3.052)	(3.073)	(2.718)	
Weekly Hours Worked	36.35	36.57	35.18	**
	(12.65)	(12.51)	(13.32)	
Weekly Earnings	252.3	260.6	208.8	***
	(152.4)	(153.6)	(137.8)	
Experience	145.8	146.8	140.5	***
	(50.96)	(49.82)	(56.28)	
In Paid Work	0.804	0.808	0.783	*
	(0.397)	(0.394)	(0.412)	
Self Employed	0.161	0.164	0.146	
	(0.367)	(0.370)	(0.353)	
Has a Partner	0.873	0.879	0.839	***
	(0.333)	(0.326)	(0.367)	
Number of Children	1.474	1.444	1.635	***
	(1.125)	(1.121)	(1.130)	
London	0.299	0.309	0.247	***
	(0.458)	(0.462)	(0.431)	
Observations	7296	6125	1171	7296

Notes: Summary statistics for the analytic sample of 7,296 individuals. Statistics are reported separately for all individuals (Column [1]), for individual that did not experience financial difficulties growing up (Column [2]) and for those that did (Column [3]). For education categories, employment and partnership, entries are in the form of percentages divided by 100. Experience is measured in months and wages and weekly earnings are in 1992 British pounds. The Self Employed row reports the percentage of individuals in paid work that are self-employed. In Column [4], *, ** and *** mean that differences between males and females are significant at the 10, 5 and 1 percent levels, respectively.

Table 18: ME Model: Ordered Probit for Educational Attainment, by SES

	[High SES]	[Low SES]
Externalizing Factor	-0.061**	-0.108*
Internalizing Factor	-0.053**	-0.032
Cognition	0.698***	0.629***
Mother Education	0.246***	0.357***
Father Education	0.297***	0.185*
No Father Info.	0.259***	0.201
Father in Skilled Occupation	0.162***	0.076
Father in Managerial Occupation	0.390***	0.282*
Working Mother	-0.002	0.069
Police Involvement	-0.416***	-0.559***
No Police Inv. Info	-0.378***	-0.406***

Notes: This table contains parameter estimates from the Ordered Probit model used to link non-cognitive skills to educational attainment with the additional control "police involvement at age 16". We estimate educational attainment on a set of observable variables along with the unobserved factors. The estimation is done separately for individuals having low-SES family backgrounds and those having high-SES family backgrounds. The coefficients on the three factors have been standardized to represent a 1 standard deviation effect. * denotes the coefficient is significant at the 10% level, ** denotes the coefficient is significant at the 5% level and *** denotes the coefficient is significant at the 1% level.

Table 19: ME Model: Log Hourly Wages, by SES

	[High SES]	[Low SES]
Externalizing Factor	0.034***	0.009
Internalizing Factor	-0.039***	-0.038*
Cognition	0.047***	0.039**
CSE	0.012	-0.009
O-Level	0.074***	0.061
A-Level	0.153***	0.039
Higher Education	0.235***	0.258***
Higher Degree	0.397***	0.428***
Partner Dummy	0.086***	0.101**
Number of Children	-0.022***	-0.025*
Experience	0.002***	0.001***
Skilled Manual Occu.	0.108***	0.086**
Skilled Non-manual Occu.	0.182***	0.115***
Managerial Occu.	0.345***	0.215***
London Dummy	0.147***	0.189***
Police Involvement	0.019	0.005
No Police Inv. Info	-0.017	0.010
Constant	1.276***	1.340***

Notes: This table contains parameter estimates from OLS regressions used to link non-cognitive skills to hourly wages with the additional control "police involvement at age 16". We regress log hourly wages on a set of observable variables along with the unobserved factors. The estimation is done separately for individuals having low-SES family backgrounds and those having high-SES family backgrounds. The coefficients on the three factors have been standardized to represent a 1 standard deviation effect. * denotes the coefficient is significant at the 10% level, ** denotes the coefficient is significant at the 5% level and *** denotes the coefficient is significant at the 1% level.

Table 20: ME Model: Log Weekly Hours Worked, by SES

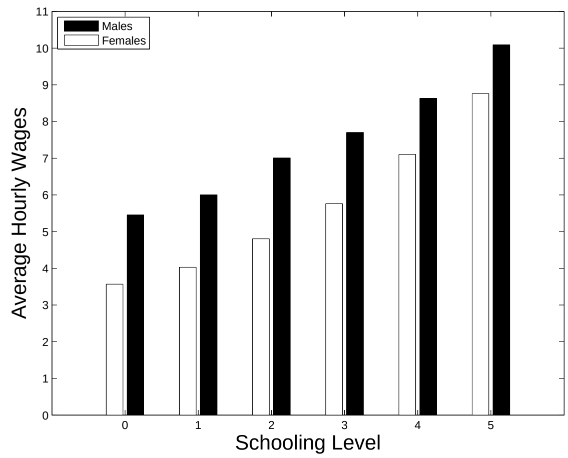
	[High SES]	[Low SES]
Externalizing Factor	0.043***	0.023
Internalizing Factor	-0.036***	-0.001
Cognition	0.002	0.036*
CSE	-0.021	-0.004
O-Level	-0.039*	-0.010
A-Level	-0.030	0.008
Higher Education	-0.069***	0.047
Higher Degree	-0.018	0.089
Partner Dummy	-0.003	-0.008
Number of Children	-0.081***	-0.087***
Experience	0.001***	0.001***
Skilled Manual Occu.	0.168***	0.109**
Skilled Non-manual Occu.	0.097***	-0.034
Managerial Occu.	0.216***	0.090*
London Dummy	0.004	0.032
Police Involvement	0.068**	0.031
No Police Inv. Info	-0.057	-0.008
Constant	3.603***	3.686***

Notes: This table contains parameter estimates from OLS regressions used to link non-cognitive skills to hours worked with the additional control "police involvement at age 16". We regress log weekly hours worked on a set of observable variables along with the unobserved factors. The estimation is done separately for individuals having low-SES family backgrounds and those having high-SES family backgrounds. The coefficients on the three factors have been standardized to represent a 1 standard deviation effect. * denotes the coefficient is significant at the 10% level, ** denotes the coefficient is significant at the 5% level and *** denotes the coefficient is significant at the 1% level.

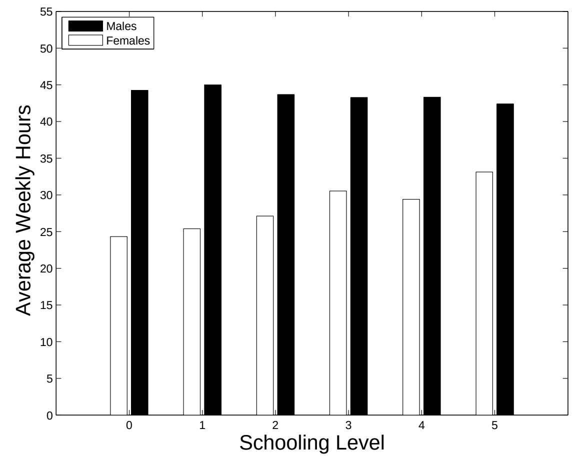
Table 21: ME Model: Linear Probability Model - Police Involvement at 16

	[High SES]	[Low SES]
Externalizing Factor	0.351***	0.244**
Internalizing Factor	-0.174***	-0.059
Cognition	-0.242***	-0.123
Mother Education	0.011	-0.521**
Father Education	-0.042	-0.199
No Father Info.	0.431*	0.349
Father in Skilled Occupation	-0.210***	-0.222*
Father in Managerial Occupation	-0.358***	-1.059*
Working Mother	0.041	0.045
Constant	-0.994***	-0.414**

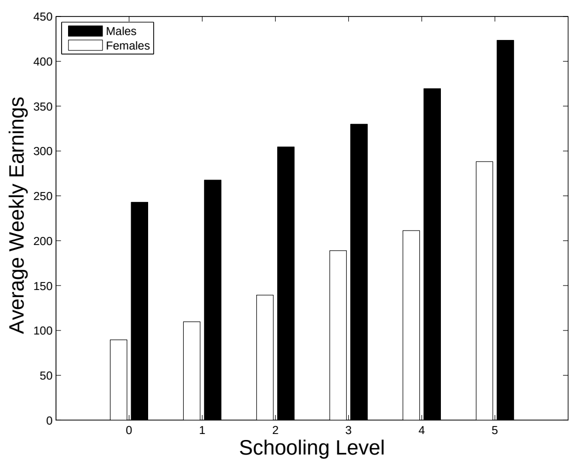
Notes: This table contains parameter estimates from a linear probability model used to link non-cognitive skills to "police involvement at age 16". We regress police involvement on a set of observable variables along with the unobserved factors. The coefficients on the three factors have been standardized to represent a 1 standard deviation effect. * denotes the coefficient is significant at the 10% level, ** denotes the coefficient is significant at the 5% level and *** denotes the coefficient is significant at the 1% level.



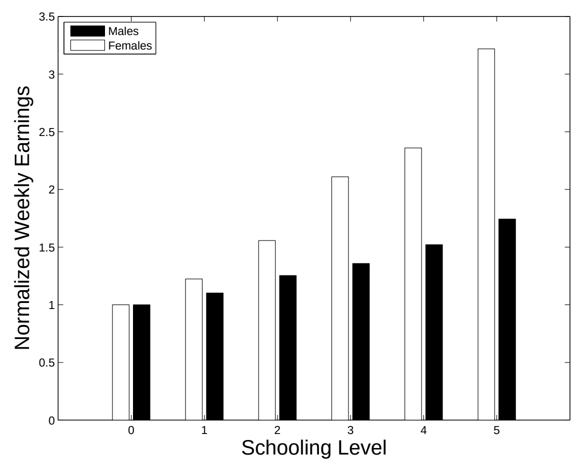
(a) Wages by schooling



(b) Hours by schooling

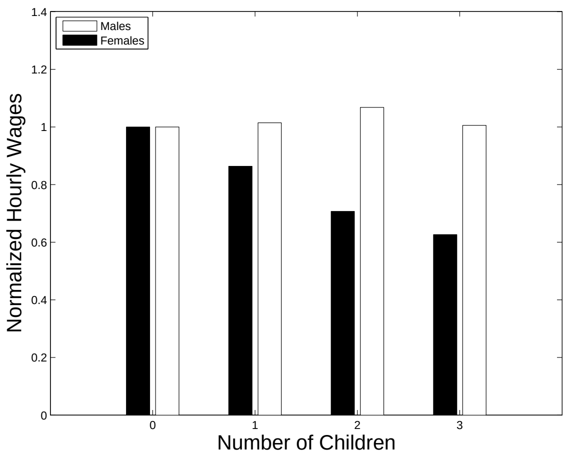


(c) Earnings by schooling

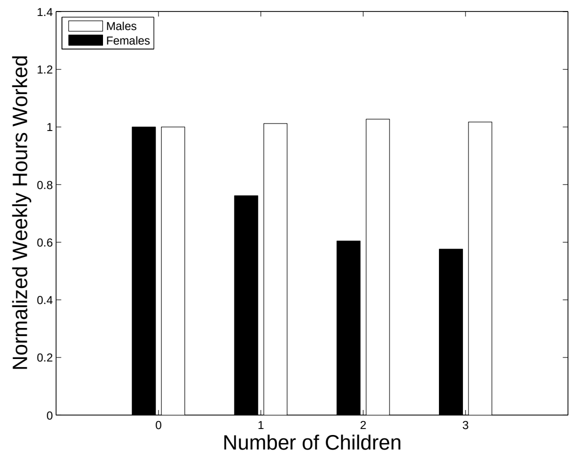


(d) Normalized earnings by schooling

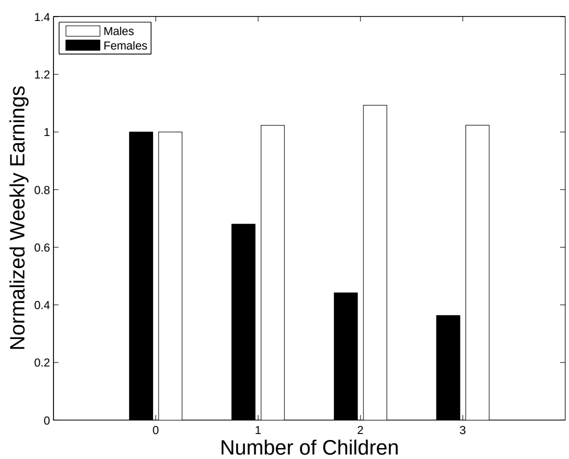
Figure 1: Gender Differences in Labor Market Outcomes by Schooling: Figure 1(a) compares hourly wages by schooling level and gender, Figure 1(b) compares weekly hours worked by schooling level and gender, , Figures 1(c) and 1(d) compares weekly earnings and normalized weekly earnings by schooling level and gender.



(a) Normalized wages by fertility

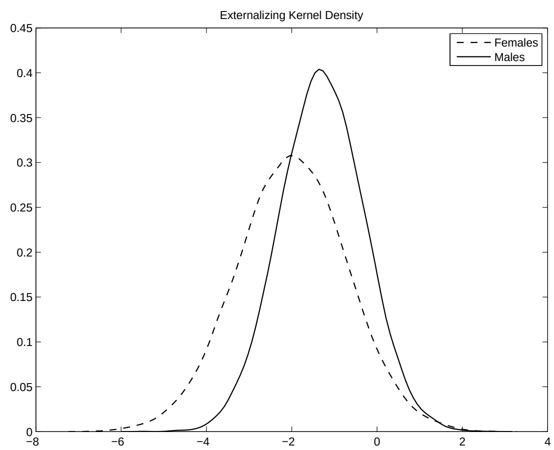


(b) Normalized hours by fertility

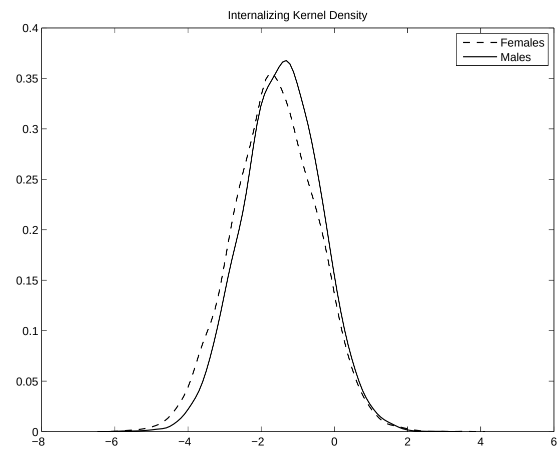


(c) Normalized earnings by fertility

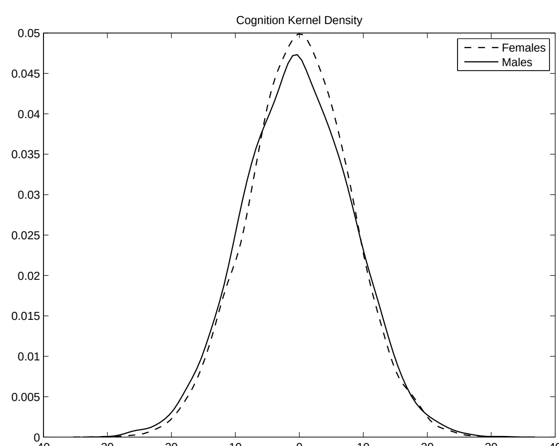
Figure 2: Gender Differences in Labor Market Outcomes by Fertility: Figure 2(a) compares hourly wages by number of children and gender, Figure 2(b) compares weekly hours worked by number of children and gender, , Figure 2(c) compares normalized weekly earnings by number of children and gender.



(a) Estimated Distribution Externalizing



(b) Estimated Distribution for Internalizing



(c) Estimated Distribution Cognition

Figure 3: GENDER DIFFERENCES IN LATENT FACTORS: Figure 3(a) shows the estimated distribution of externalizing behavior by gender. Figure 3(b) shows the estimated distribution of internalizing behavior by gender. Figure 3(c) shows the estimated distribution of cognition by gender.

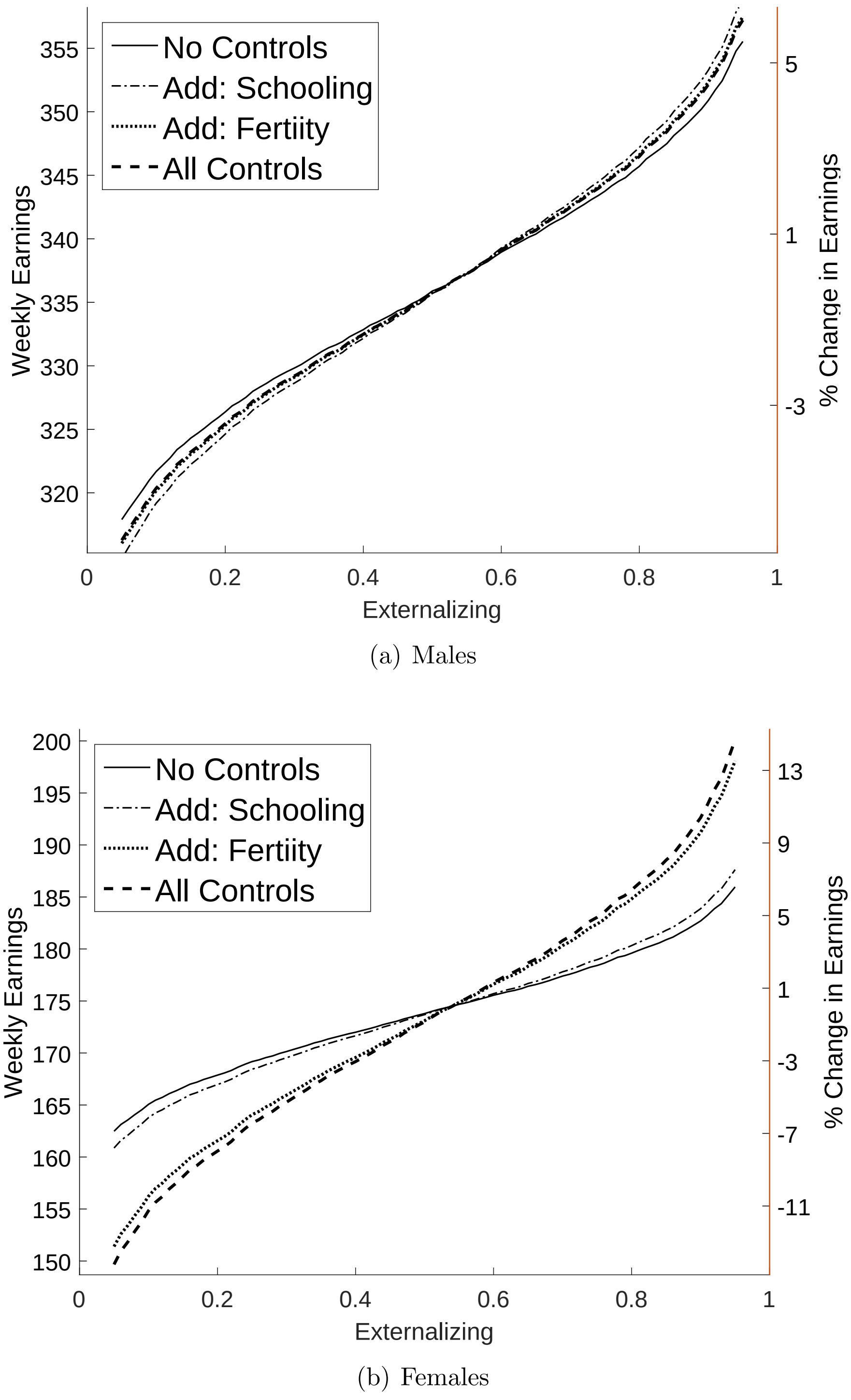


Figure 4: Decomposition of Effects of Externalizing on Weekly Earnings: Figure 4 visualizes the results from regressing weekly earnings on a varying set of controls presented in Tables 13 and 14. It illustrates how the predicted weekly earnings in regression models with different sets of controls vary, when we increase the externalizing from the lowest 5th percentile to the highest 95th percentile, keeping other latent skills and covariates at the population median.