Genes, Education, and Labor Market Outcomes: Evidence from the Health and Retirement Study*

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Abstract: Recent advances have led to the discovery of specific genetic variants that predict educational attainment. We study how these variants, summarized as a linear index — known as a *polygenic score* — are associated with human capital accumulation and labor market outcomes in the Health and Retirement Study (HRS). We present two main sets of results. First, we find evidence that the genetic factors measured by this score interact strongly with childhood socioeconomic status in determining educational outcomes. In particular, while the polygenic score predicts higher rates of college graduation on average, this relationship is substantially stronger for individuals who grew up in households with higher socioeconomic status relative to those who grew up in poorer households. Second, the polygenic score predicts labor earnings even after adjusting for completed education, with larger returns in more recent decades. These patterns suggest that the genetic traits that promote education might allow workers to better accommodate ongoing skill biased technological change. Consistent with this interpretation, we find a positive association between the polygenic score and non-routine analytic tasks that have benefited from the introduction of new technologies. Nonetheless, the college premium remains a dominant determinant of earnings differences at all levels of the polygenic score. Given the role of childhood SES in predicting college attainment, this raises concerns about wasted potential arising from limited household resources.

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1 Introduction

Economists generally accept that the skills rewarded in the labor market arise from a combination of endowed abilities, economic environments, and endogenous human capital investments. Endowments, environments and investments almost certainly interact in complicated ways, transforming the distribution of abilities drawn at birth into a distribution of education, wages, and labor supply outcomes over the life-cycle.

Understanding this web of interactions and its implications for economic inequality has been a long-standing project in labor economics (Mincer, 1958; Becker and Chiswick, 1966; Griliches and Mason, 1972). Selecting an appropriate policy response to inequality requires an accurate diagnosis of its origins. Poor households possess limited resources for human capital investment, which naturally suggests a role for redistributive policies. However, disparities in endowments might also play a part. If individuals with unfavorable endowments do not acquire more human capital for reasons unrelated to resources (e.g. lower returns to these investments), then simply relaxing resource constraints and expanding access to education may not substantially reduce inequality. However, understanding the mapping between endowments, investments, and economic outcomes is challenging: ability is notoriously difficult to measure and typical proxies (such as IQ test scores) are subject to the critique that they reflect earlier investments.

A common assumption is that genes and other biological factors at least partially determine heterogeneity in ability across individuals (e.g. Todd and Wolpin (2003)). In this study we exploit recent advances in genetics to explore the relationship between a genetic index, educational attainment, and labor market outcomes in the Health and Retirement Study (*HRS*). Specifically, we utilize a polygenic score (a weighted sum of individual genetic markers) constructed with the results from Lee et al. (2018) to predict educational attainment.[1] The markers most heavily weighted in this index are linked to early brain development, as well as processes affecting neural communication (Lee et al., 2018; Okbay et al., 2016). We interpret the polygenic score as summarizing a subset of the genetic factors that influence traits relevant for human capital accumulation.[2]

[1]Results reported in Okbay et al. (2016) and Lee et al. (2018) represent the cutting edge in behavioral genetics relating specific genetic variants to education. We discuss these papers and the research leading up to them in Section 2, where we provide further details on the genetic data used in this project. Additional background information is in Appendix A.

[2]We explicitly avoid describing the polygenic score as a measure of "ability," since this term may be too broad and may oversimplify the complexities of genetic endowments. We also want to avoid conflating our interpretation of the polygenic score with the broader definition of "ability" as it is viewed in labor economics. For example, in *Human Capital*, Becker (1975) defines ability as the collection of all factors that determine persistent differences in economic outcomes given the same profile of human capital investments. More formally Becker (1975) considers earnings, Y, as a function of "unskilled ability" X, human capital

Pairing this score with rich longitudinal data allows us to test propositions about the role of individual endowments in shaping education and labor market outcomes. Specifically, we examine whether childhood environments interact with genetic endowments in determining educational outcomes, and whether these endowments are associated with economic outcomes beyond their relationship with completed schooling. In empirical labor economics, genetic factors and other endowments are typically subsumed into an error term, averaged out with additive fixed-effects, or relegated to a "black box" of permanent unobserved heterogeneity that must be integrated out of econometric models (Lillard and Willis, 1978).[3] In such approaches the structure of human capital endowments, together with the nature of their interactions with the economic environment, is assumed rather than observed.[4] This may be appropriate if the goal is to reduce bias in estimation by controlling for omitted factors. However, this approach is insufficient if our goal is to learn about the structure of ability and resulting implications for policy.

A large literature uses test scores such as IQ or AFQT (Armed Forces Qualification Test) as proxies for the cognitive abilities relevant for education and labor market outcomes. However, investments and environmental factors (e.g., childhood poverty) can significantly influence these proxies, making it difficult to interpret their variation across individuals (Flynn, 1987; Turkheimer et al., 2003; Todd and Wolpin, 2007; Mani et al., 2013).[5] Among other things, this means that two individuals with similar cognitive test scores but different childhood circumstances are unlikely to have started with the same underlying human capital endowments. Reliance on these proxies may therefore lead the analyst to mis-attribute observed disparities in economic outcomes to differences in ability endowments rather than earlier investments. In turn, this could lead to incorrect conclusions on the returns to human capital investments (e.g., public education, college subsidies, etc.). In contrast, even though the genetic index we study is undoubtedly correlated with parental characteristics, its use is not subject to the critique that it is the *product* of endogenous investments, since it is fixed at conception.[6]

investments, C, and the rate of return on investments, r: $Y = X + rC$ (p. 62). In this framework, ability consists of all factors that influence the pair (X, r). Such factors may include genetic endowments, but are certainly not limited to genetic or other biological influences.

[3]This point suggests that the polygenic score should capture some of the information that is contained in individual fixed effects. In results available in Appendix B, we show that this is the case, which provides evidence for the link between previously unobserved heterogeneity and the information contained in the polygenic score.

[4]Considering again Becker's formulation $Y = X + rC$, it is often assumed that unobserved ability enters exclusively through "unskilled ability." (X), so that a linear fixed effects model controls for ability.

[5]Proxies for endowments measured among children or newborns are also subject to this type of critique (Almond and Currie, 2011).

[6]As we explain throughout the paper, the genetic index is correlated with environments and investments, since parents pass on their genes in addition to shaping environments and making investments. Nevertheless,

We present two main sets of results. First, we document the association between the polygenic score and educational attainment, and demonstrate that this association differs by childhood SES. Using the HRS data, we replicate the strong relationship between the genetic score and educational attainment found in past studies (Lee et al., 2018; Okbay et al., 2016). A one-standard-deviation increase in the polygenic score predicts between 0.59 and 0.84 additional years of education, while variation in the score accounts for 3.4% to 7.5% of the variation in years of schooling, depending on the control set. After this replication exercise, we turn to new analyses enabled by the availability of molecular genetic data for HRS respondents.[7] A surprising descriptive fact emerges in the relationship between the polygenic score and retrospective measures of childhood SES. While the polygenic score is positively correlated with childhood SES, the distribution of the score is strikingly similar across SES groups. This empirical pattern makes it possible to compare economic outcomes for a large set of individuals with similar genetic scores, but different childhood SES. We find that high childhood SES seems to reduce the association between genes and the probability of completing high school, while increasing the genetic gradient in the propensity to earn a college degree. These findings could reflect different patterns of substitutability and complementarity between genes and family resources in producing early versus later human capital outcomes. More broadly, these SES interactions underscore the importance of examining gene-environment interactions to understand economic inequality and the distributional consequences of interventions.

Understanding the role of endowments is particularly important in light of the large earnings premium associated with a college degree and its growth over the last several decades. Given substantial returns to schooling, we expect genetic endowments for education to unconditionally predict earnings. However, the factors that allow one to more easily acquire schooling may also permit greater economic success, even conditional on a particular level of investment (better cognitive endowments, greater persistence, etc.). This motivates our second set of new analyses which test whether — and through what mechanisms — the genetic factors associated with education independently predict better labor market outcomes. This question is particularly relevant given the sizable interactions between childhood SES

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the fact that environments and investments do not change the genetic score offers an important exclusion restriction. This point is fleshed out in greater detail in Section 3.6 and is formalized in a simple econometric model provided in Appendix C.

[7] According to studies that compare identical and non-identical twins to assess the role of genetic factors in explaining behavior and outcomes, roughly 25-40% of the variation in educational attainment can be attributed to genetic factors. Such studies treat genetic factors as unobservable and decompose the variance of education into genetic and environmental components. The incremental R^2 of the EA score is substantially below the fraction of variation explained by genes in these twins studies, suggesting that the score either does not capture all genetic factors, or does so with a non-trivial amount of measurement error. We elaborate on this issue in Section 2.

and genetic endowments. While it is certainly possible that individuals with favorable endowments realize their full earnings potential even without a college degree, it may also be the case that individuals with high polygenic scores are unable to fully compensate for the lack of a college degree in the labor market. If so, disparities in childhood SES may erect barriers to college completion and lead to the wastage of economic talent.

Using administrative records that cover the lifecycle, we find a strong relationship between the polygenic score and labor market earnings, even after controlling for completed education. The returns to these genetic endowments appear to rise over time, coinciding with the rise in income inequality after 1980. Accounting for degree and years of schooling, a one standard deviation increase in the score is associated with a 4.8 percent increase in earnings after 1980. These results are consistent with recent literature on income inequality showing not only an increase in the college premium, but also a rise in the residual wage variance within educational groups (Lemieux, 2006). We also find a positive association between the score and the kinds of non-routine job tasks that benefited from computerization and the development of more advanced information technologies (Autor, Levy, and Murnane, 2003). This provides suggestive evidence that the endowments linked to more educational attainment may allow individuals to either better adapt to new technologies, or specialize in tasks that more strongly complement these new technologies. Nonetheless, despite returns to these endowments for those with and without a college degree, the average college premium remains large across all values of the polygenic score. Poor childhood environments appear to squander the human potential of individuals with favorable genetic endowments by preventing access to increasingly lucrative educational pathways.

This paper adds to an emerging literature examining molecular genetic associations with economic outcomes.[8] However, to our knowledge, this is the first study to estimate the returns to genetic factors associated with education using micro genetic data and disaggregated measures of earnings and job tasks across cohorts. Our results therefore offer two broad contributions that link the literature on behavioral genetics to the economics literature on human capital, ability, and economic outcomes. First, our results demonstrate that several core findings obtained with proxies of cognitive ability continue to hold with a biological measure of endowments that predicts schooling and is fixed at conception. Even if genetic data offered no other insights, this would provide some evidence that test scores capture useful information on endowments, and not just post-birth investments. A second contribution, however, consists of novel results on the origin and function of heterogeneity

[8]For example, in a recent paper, Schmitz and Conley (2016) demonstrate that the effect of military service on educational attainment is moderated by the same polygenic score considered here. In Section 2, we discuss more papers in this line of research.

in the earnings distribution. Our results on the rising genetic earnings premium (controlling for education) implicate genetic heterogeneity in a series of important and well-documented patterns in labor economics. In particular, the same factors associated with greater human capital accumulation also appear to be increasingly important for earnings during a period of technological and structural change in the economy.

Our results also illustrate how genetic measures can be used to generate novel insights about the importance of interactions between endowments and childhood environments in the study of economic inequality. We provide some of the first evidence using molecular genetic measures that people with favorable genetic endowments may face barriers to exploiting their potential if they are born into poor families.[9] This finding relates to a larger literature exploring similar interactions using different measures of endowments, or using alternate methods to measure genetic contributions. Leibowitz (1974) is an early example of research recognizing heterogeneity in returns to ability measured by IQ. Further contributions have emphasized the consequences of such interactions for inequality. Consistent with our findings, Guo and Stearns (2002) use a twins-study design to provide evidence that resource-poor environments imply lower returns to genetic endowments. Gene-environment interactions could also explain why genetic influences on IQ are relatively strong for high-SES children, a phenomenon known as the Scarr-Rowe Hypothesis (Scarr-Salapatek, 1971; Nisbett et al., 2012; Bates, Lewis, and Weiss, 2013; Kirkpatrick, McGue, and Iacono, 2015; Tucker-Drob and Bates, 2016). This would occur if returns to genetic endowments (as measured by IQ) are stronger in resource-rich households, which is consistent with our findings on gene-environment interactions and college education.[10]

Our results on gene-environment interactions are also linked to work on treatment effect heterogeneity, which has emerged as an important topic in econometrics and applied work. Heckman and Vytlacil (2005) develop econometric methods for the case of heterogeneous treatment effects, either due to choices or responses. Many studies document a range of heterogeneous responses to interventions related to labor, including welfare reform (Bitler, Gelbach, and Hoynes, 2006), information about payoffs to education (Wiswall and Zafar, 2015) and education subsidies (Todd and Wolpin, 2006). Related, Keane, Moffitt, and Runkle

[9]Belsky et al. (2016) study a sample of New Zealanders and track outcomes from birth through the age of 38. Their findings suggest that there may be a weaker association between genetic ability and lifetime success for high-SES households. A benefit of our analysis is that, using a richer data set, we are able to examine disaggregated measures of labor market success, including labor supply and earnings over the entire life-cycle.

[10]Relatedly, children with high polygenic scores are more likely to grow up in resource-rich environments, meaning they enjoy higher returns to their genetic endowments compared to similarly endowed children in poorer households. Coupled with assortative mating on IQ, inequality in IQ should rise over time, which is a pattern that has been documented in Dickens and Flynn (2001).

(1988) study how individual-level heterogeneity affects responses to economic shocks, in their case labor supply decisions over the business cycle. In our case, responses to technological shocks may in part be explained by heterogeneity in genetic endowments.

The remainder of the paper is organized as follows. In Section 2, we discuss recent developments in behavioral genetics (and their limits), focusing on techniques used to establish links between genes and economic outcomes. In Section 3, we relate the polygenic score to education and childhood SES. In Section 4, we discuss how the polygenic score relates to labor market outcomes. Section 5 concludes.

2 Genetic Data and Their Limits

In this section, we provide some basic information about the molecular genetic data we use in this study. We also discuss some problems, points of clarification and interpretational difficulties. Appendix A provides additional detail.[11]

2.1 Genetic Data and Genome-Wide Association Studies

The human genome consists of approximately 3 billion nucleotide pairs spread out over 23 chromosomes pairs. An individual possesses two copies of each chromosome, inheriting one copy from each of its parents.[12] The base pairs are the "rungs on the ladder" of classic double-helix structure. Genes are subsequences of these base pairs that often contain the instructions for synthesizing proteins. There are about 50,000 genes in the human genome. At the vast majority of base pair locations in the genome (about 99 percent), there is no variation across individuals in the nucleotide. At the remaining locations (less than 1 percent), the base pair may differ across individuals. Such locations are referred to as single-nucleotide polymorphisms (SNPs, pronounced "snips").

A major task of behavioral genetics involves determining which, if any, of these SNPs are associated with behavioral outcomes. Genome-wide association studies (GWAS) provide one tool for estimating these associations. Under the GWAS methodology, researchers scan the entire genome for SNPs that are associated with a particular phenotype (trait or outcome). Variation at a particular SNP is measured by a count variable indicating how many copies of a particular base pair molecule an individual possesses at that genetic location. These variables can take the values 0, 1, or 2 because an individual has two copies of each chromosome. The

[11] We are grateful to Aysu Okbay for clarifying a number of questions on the description we provide in this section. However, any erroneous statements are the sole responsibility of the authors.

[12] Most of the background information presented here on the human genome follows Beauchamp et al. (2011) and Benjamin et al. (2012).

outcome of interest is typically regressed on each observed SNP count (one at a time), while also controlling for principal components of the full matrix of SNP data. As indicated by Price et al. (2006) (and discussed at length in Benjamin et al. (2012) in the context of economic outcomes) the principal components can correct for population stratification and account for genetic differences across ethnic groups. The presence of these controls limits the concern that gene-behavior associations reflect associations with specific ethnic ancestry groups as opposed to specific biological pathways. In our subsequent analysis we always control for population stratification using the first 10 principal components of the full matrix of genetic data.[13]

While GWAS studies have produced a number of credible and replicable gene-outcome associations, GWAS results for educational attainment have only emerged recently. After documenting the first genome-wide significant associations for education (Rietveld et al., 2013), the Social Science and Genetics Association Consortium extended their analysis to perform an educational attainment GWAS with larger sample sizes, starting with Okbay et al. (2016) (N = 293,723) which discovered 74 SNPs with associations strong enough to be considered genome-wide significant.[14] The score we study in this paper is based on results from the most recent education GWAS from this group, Lee et al. (2018), featuring a discovery sample of over 1.1 million people. Many of these SNPs were linked to biological processes known to be involved in fetal brain development. Evidence presented in Okbay et al. (2016) and Lee et al. (2018) heavily implicates cognitive mechanisms in the biological pathways that link the score to educational attainment. Lee et al. (2018) find that some of the significant SNPs tend to be expressed prenatally in brain tissues, while others are expressed throughout the lifecycle. This second group of SNPs tend to be found in genes that "encode proteins that carry out neurophysiological functions such as neurotransmitter secretion, the activation of ion channels and metabotropic pathways, and synaptic plasticity," (Lee et al. (2018), p. 1114).

GWAS results are often aggregated into polygenic scores for the purposes of prediction and statistical analysis. These scores are linear combinations of individual SNP count variables, weighted by their GWAS coefficients. Importantly, although HRS data are used in the

[13]The use of 10 principal components is standard practice in the literature (Okbay et al., 2016). Omitting the principal components, though not at all advisable as a general approach given concerns about population stratification, does not affect our results in this paper, suggesting that other controls adequately capture the type of stratification that might be more substantial or problematic in other data sets.

[14]Many single-SNP associations from earlier genetic studies have failed to replicate. As discussed in Hewitt (2012), this problem often emerged because earlier genetic studies were underpowered to detect reasonable association sizes, and because of failures to correct for multiple hypothesis testing. Given these concerns, modern GWAS studies adopt strict conventions before considering a single-SNP association to be "genome-wide significant." A convention benchmark for genome-wide significance is a p-value that is less than 5×10^{-8}.

published results for Lee et al. (2018), the score used here has been calculated on the basis of GWAS results without HRS data, ensuring that the score does not mechanically predict educational outcomes. We refer to the score we use as the *EA score*, where EA stands for "educational attainment." Since this is the only polygenic score we examine in this paper, we use the terms "*EA score*," "*polygenic score*," and "*genetic score*" interchangeably.[15]

Existing work suggests that polygenic scores usefully summarize genetic information contained by some of the SNPs associated with education. Most existing studies work with earlier, less predictive polygenic scores based on the results of Rietveld et al. (2013) and Okbay et al. (2016). Conley and Domingue (2016) find evidence of changing patterns of assortative mating across cohorts on the basis of a polygenic score for education, while Schmitz and Conley (2016) show that genetic heterogeneity can moderate the impact of military service during the Vietnam War on subsequent educational attainment. Closer to our work, Belsky et al. (2016) use the polygenic score to predict childhood and adolescents developmental milestones and cognitive abilities. They examine a sample of 918 New Zealanders and show that a similar polygenic score not only predicts education, but also an index of adult success conditional on education. In relating genes predicting education to an aggregated measure of success in the labor market, their study provides important cross-validation to our own work, though with a different sample and a substantially different set of outcomes and research questions. Finally, Barth, Papageorge, and Thom (2018) show evidence that the EA score predicts wealth in part through financial decision-making and probabilistic thinking.

2.2 Limitations and Interpretational Challenges

We discuss five important caveats and points of clarification regarding our use of the polygenic score for education. First, the genetic variants used in the construction of this genetic score are not located on sex chromosomes. For this reason, the distribution of these variants should be identical across men and women. In our labor market analysis, we focus on males to bypass considerable issues associated with selection into employment. However, we exam-

[15]The polygenic score that we use is constructed using all of the SNPs that we observe, and not just those that attain genome-wide significance. This follows the practice in Okbay et al. (2016) and Lee et al. (2018). Polygenic scores based on all SNPs have performed better at predicting educational attainment in holdout samples. The score is constructed with the LDpred method (using parameters outlined in Okbay, Benjamin, and Visscher (2018)), which is one way to deal with the possibility of "double-counting" given correlations between individual SNPs (Ware et al., 2017; Vilhjálmsson et al., 2015). While the weights assigned to each SNP typically vary across methods, these weights are usually based on the strength of a SNP's association with the outcome of interest and the joint covariance matrix of the SNPs. In a series of robustness checks presented in Appendix B we show that main results are qualitatively similar if we use alternative scores, e.g., earlier versions discovered on smaller samples, or by using different methods to combine them. This is important as it suggests that our key results will not change qualitatively as the field advances and more genes are discovered to be genome-wide significant.

ine both men and women when studying educational investments, the goal being to restrict the sample only when there is a compelling reason to do so. In Appendix B, we explore possible gender differences in how the EA score relates to years of education. There are some specifications showing larger coefficients on the EA score for men compared to women.[16] An obvious direction for future research would be to study gender differences in returns and, more generally, how the genetic score interacts with female labor supply decisions and labor outcomes.

A second point is that the polygenic score we use was discovered on a sample of individuals of European ancestry. It has been shown in earlier work that a polygenic score discovered on one ethnic group is relatively less predictive if applied to other ethnic groups. A striking example is a polygenic score for height discovered on a sample of Europeans which erroneously predicts that individuals of African ancestry are on average substantially shorter than genetic Europeans (Martin et al., 2017). It would therefore be misleading and irresponsible to use the EA score we use in this paper to analyze individuals of non-European ancestry. Thus, we limit our sample to individuals of European ancestry as categorized by the HRS. It should be noted that with this restriction, the principal components of the genetic data help to account for intra-European ethnic differences.

Third, we do not claim to estimate *causal effects* of particular genetic variants. Any gene-outcome association that we observe in general reflects a combination of a direct effect and an indirect effect operating through the environments that parents make for their children.[17] Parents with advantageous genetic endowments (some of which they pass on to their children) are more likely to have the resources or capacity to create better environments. Indeed, Kong, Thorleifsson et al. (2018) find that parental genotypes that are not passed on to their children still predict children's education, suggesting the operation of this indirect channel.[18] Even so, an individual's genetic make-up is not *changed* by human capital investments. In contrast, IQ and other cognitive test scores are subject to the critique that they reflect environmental factors, such as earlier human capital investments. Indeed, Bharadwaj, Løken, and Neilson (2013) find that variation in health care received by newborns has an impact on academic achievement years later.[19] Genetic indices are not subject to this critique since they are fixed

[16]Given the argument that many gender differences could be socially constructed, Molina (2016) suggests that gender can be seen as an environmental factor and that gender differences in coefficients reflect gene-by-environment interactions.

[17]A related identification problem is that parents can react to the genetic endowment of the child and reinforce or compensate their investments. In the literature this is called a gene-environment correlation (Plomin, DeFries, and Loehlin, 1977).

[18]See Koellinger and Harden. (2018) for a further discussion of the implications of this finding.

[19]Even birth weight, another proxy of innate endowments that has been used in prior literature, is not immune to this critique as it reflects *in utero* investments, e.g., mother's smoking behavior (Lien and Evans, 2005), exposure to pollutants (Currie, Neidell, and Schmieder, 2009), stress during pregnancy (Camacho,

at conception. As we elaborate below (see Appendix C and the discussion in Section 3.6), this feature of genetic endowments generates an important exclusion restriction which can be used to correctly sign gene-environment interactions. Moreover, there is strong evidence from a variety of studies showing that much of the relationship between an earlier EA score and educational attainment remains, even after controlling for family fixed effects with data on siblings (Domingue et al., 2015; Rietveld et al., 2014).[20] If the relationship between the score and education merely reflected family environments, we would expect between-family variation to be much more strongly predictive of outcomes. Finally, controlling for principal components helps to alleviate the concern that we are merely capturing ethnic differences in social norms surrounding education.

A fourth limitation concerns the variation in observed outcomes that is explained by the polygenic score. Twin studies have established that roughly 25-40 percent of the variation in educational attainment can be attributed to genetic endowments, suggesting that genes represent an important source of human capital endowments (Branigan, McCallum, and Freese, 2013).[21] In our sample of HRS respondents, we show that the polygenic score can explain up to 7.5% of the variation in educational attainment, i.e., roughly 19-30% of the total variation that other methods suggest is attributable to genes. This discrepancy is often referred to as the "missing heritability problem" (Eichler et al., 2010; Zuk et al., 2012) and may arise from a variety of causes, including limited power to detect rare variants or variants with small association sizes, failure to account for genetic interactions, and genetic variation that is not captured by SNP-level differences (e.g. copy-number polymorphic duplications). In practice, the missing heritability problem means that it is difficult to use the polygenic score to draw conclusions about the relative importance of genetic endowments versus environments in generating economic outcomes. This is a drawback of analyses using polygenic scores relative to twin study methods.[22] On the other hand, observed genetic variants allow us to more directly estimate the size and directions of gene-environment interactions (e.g., differences in gene-education gradients by childhood SES), and explicitly identify the variants involved in such interactions.

2008; Currie and Rossin-Slater, 2013) or mothers' own health (Costa, 1998). See also Aizer and Currie (2014) for a recent discussion.

[20] In a recent contribution, Ronda et al. (2019) use Danish data to examine within-sibling-pair differences in the EA score and educational outcomes. They find that controlling for mother's education, which we do in our analyses, eliminates differences in within-sibling versus between-family coefficients on the EA score by 70%.

[21] Taubman (1976) is an early contribution using data on twins, who have similar or identical genotypes, to assess the amount of variation in earnings attributable to genes.

[22] Related, given that the polygenic score is a noisy measure of the full set of genetic endowments related to education, it would be misleading to draw conclusions about necessary or sufficient scores for economic outcomes, e.g., whether above a certain threshold individuals are guaranteed to attain a college degree.

Fifth, there are interpretational challenges in using the polygenic score in economic analysis. The polygenic score is a linear index of the genetic variants that predict educational attainment. As discussed in the Introduction, we interpret the polygenic score as measuring a subset of genetically endowed abilities relevant for educational attainment, such as a facility with learning or acquiring new skills. We purposefully refrain from describing the polygenic score as ability or as a measure of cognitive ability, which is likely to be misleading and too simplistic. One reason is that the polygenic score is a single aggregate measure, which is at odds with widespread evidence that ability is best thought of as multi-dimensional with different returns depending on the economic outcome in question. In particular, there are distinct cognitive abilities associated with human capital accumulation and labor market success (e.g., attention, language, visuospatial skills, motor skills, executive function and memory) each possessing different associations with economic outcomes (Willis and Rosen, 1979; Heckman, 1995; Cawley et al., 1997).[23] In addition, socio-emotional skills (sometimes known as non-cognitive or "soft" skills) play crucial roles in education and labor outcomes (Heckman and Rubinstein, 2001).[24] Thus, it would make little sense to categorize an individual with a high polygenic score as "high ability" or to equate the polygenic score with cognitive ability.[25] Second, it is not clear how genes generate economic outcomes, either on their own or through interactions with the environment. As discussed, pathway analyses suggest that the genes most heavily weighted in the EA score are implicated in the development of brain tissue and in processes related to neural communication. While this strongly suggests that cognitive processes are involved, we lack a comprehensive understanding of the biological pathways at play. The EA score almost surely includes factors related to skills that are directly related to cognition and facilitate schooling, but may (or may not) be productive in other contexts, such as the labor market.[26] That said, one of the benefits of examining the EA score in a rich data set such as the HRS is that it allows us to examine relationships

[23]On multidimensionality, Willis and Rosen (1979) emphasize manual skill, which they distinguish from academic skill.

[24]Later contributions to this literature include Kautz et al. (2014) and Humphries and Kosse (2017).

[25]In Appendix D, we show that a measure of cognition that is available for HRS respondents is positively associated with the EA score, but only weakly so (with a correlation coefficient of roughly 0.23). Moreover, the EA score predicts education and earnings even after we control for the cognitive test score, suggesting that the EA score captures additional factors relevant to educational attainment. However, the comparison of the EA score with the cognitive test score in the HRS is difficult to interpret since the latter is meant to capture cognitive decline. A more useful exercise would be to compare the EA score with scores from tests designed to measure cognition, such as the AFQT, which is not available in the HRS.

[26]Indeed, Papageorge, Ronda, and Zheng (2017) provide evidence that a socio-emotional skill known as *externalizing behavior* and linked to aggression predicts higher wages despite being associated with lower educational attainment. If it has a genetic basis, it would enter negatively into the polygenic score despite its value on the labor market, further underscoring the need to interpret the polygenic score as a measure of genetic factors that influence some skills associated with educational attainment, but not as a broad measure of "ability."

between the EA score and several critical economic variables. Doing so provides valuable insights into how these genetic variants function over the lifecycle, which offers clues on mechanisms underlying their relationship to human capital accumulation.

3 Genes, Education, and Childhood SES

3.1 The HRS Sample and the Genetic Score

The HRS is a longitudinal panel study that follows over 20,000 Americans at least 50 years of age, as well as their spouses. Surveys began in 1992 and occur every two years. The HRS collected genetic samples from 18,994 individuals over the course of four waves (2006, 2008, 2010, 2012). Our analytic sample only includes individuals genotyped in 2006 and 2008.[27] Individuals in the genotyped sample tend to be born in younger birth cohorts, since survival until at least 2006 is required for inclusion. Moreover, women and individuals with more education were more likely to agree to the collection of genetic data.

Our main analysis sample includes all genetically European individuals born before 1965 with non-missing genetic and education data. For reasons outlined in Section 2, we restrict the sample to respondents of European ancestry since the polygenic score we use here was discovered in a sample of consisting solely of genetic Europeans.[28] The resulting sample includes 8,537 individuals. Table 1 provides some basic descriptives on demographic and educational variables. The mean level of educational attainment is about 13 years, with 13 percent of the sample failing to graduate from high school or obtain a GED and about 25 percent of the sample earning at least a four year college degree. Roughly 42 percent of the sample is male.

Table 1 also provides descriptive statistics on parental education, as well as a series of categorical variables describing health and various aspects of the SES of the respondent during childhood. These measures include a self-reported five-point scale for health during childhood, a variable indicating the SES of the respondent's family (*Well off*, *Average*, or *Poor*), as well variables indicating whether the respondent's family suffered various negative economic shocks (moving due to hardship, asking other families for help, or experiencing

[27] While genetic data for the 2010 and 2012 waves are available, the polygenic score based on the results of Lee et al. (2018) and the LDpred method has only been constructed for the respondents genotyped in 2006 and 2008. In Appendix B, we provide further detail and show that our main results continue to hold if we use a less predictive score constructed with a different methodology for individuals from all four available waves.

[28] As part of the genetic data release, the HRS classifies certain individuals as being of European descent based on their genetic ancestry. Polygenic scores have been publicly released for 12,090 individuals from the 2006, 2008, 2010, and 2012 waves who have been identified as having genetic European ancestry.

an extended period of paternal unemployment or economic inactivity). We also construct a father's income variable. To do this, we first obtain HRS survey responses on the usual occupation of the respondent's father (when the respondent was age 16). This father occupation variable is then matched with average labor income data from the 1960 census for prime-age male workers to construct an occupation-specific income variable.[29]

We measure earned income using records from the Master Earnings File (MEF) of the Social Security Administration (SSA) that have been linked to the HRS.[30] The MEF data span the period 1951-2013 and combine reports from employers with Internal Revenue Service (IRS) documents such as W-2 forms to provide a sum of "regular wages and salaries, tips, self-employment income, and deferred compensation" (Olsen and Hudson, 2009). The earnings records are top-coded at the maximum income subject to Social Security taxes in each year. When possible, we adjust for this by replacing top-coded amounts with the average level of earnings that exceed the top-code for each year based on the Current Population Survey (CPS).[31] As indicated in Table 1, the median real income for a person-year in our sample is \$55,295, while the 25th and 75th percentiles are \$34,173 and \$75,005, respectively. Figure 1 plots average earnings for each age in our sample separately for individuals with and without a college degree. The data follow a familiar hump-shaped pattern, with earnings starting at low levels early in life, reaching a peak around age 50 for less educated individuals and closer to age 60 for more educated individuals. For less educated individuals, earnings decline as individuals age and reduce their labor supply later in life.[32]

Turning to genetic data, Figure 2 presents a plot of the (kernel-smoothed) density of the EA score variable in our sample. Values of the score have been demeaned and re-scaled to measure standard deviations relative to the mean. Figure 2 suggests that the distribution of the EA score appears to be approximately normally distributed and symmetric.[33]

Unless otherwise noted, all regressions include a full set of dummy variables for birth

[29] These retrospective childhood SES measures are discussed in greater detail in Section 3.3. We use the IPUMS release of the 1960 U.S. Census data (Ruggles et al., 2018) to estimate the average income for each father's occupation group.

[30] These data are found in the *Respondent Cross-Year Summary Earnings* file of the HRS.

[31] We use the IPUMS release of the CPS data for the years 1962-2013 (Ruggles et al., 2018). While the SSA data offer rich administrative records over the life-cycle, they are top-coded based on the taxable maximum for Social Security taxes in each year. This top-coded amount has changed over time, as described in Olsen and Hudson (2009). Appendix B provides additional details on top-coding and our correction for top-coding.

[32] In Appendix B, we replicate a subset of our analyses using HRS income data. Because the HRS data contain only contemporaneous self-reported income, we cannot use them to estimate specifications related to lifetime income, which we are able to do with the SSA data. However, the HRS income data are less aggressively top-coded than the SSA data, which provides one possible advantage. The consistency of results across data sets suggests that top-coding patterns are not a significant driver of our main results.

[33] In a formal χ^2 test of normality based on skewness and kurtosis, we fail to reject the null hypothesis that the EA score is normally distributed in our sample with p-value=0.2647.

year, a male dummy, and interactions between the birth year and male dummies. Our basic control set also includes the first 10 principal components of the full matrix of genetic data. As noted in Section 2, these variables help to control for possible stratification of the score by ethnic ancestry group differences that exist among the broad category of individuals of European descent. To account for non-random selection into the genetic sample, all regressions are weighted using sampling weights that have been adjusted by the inverse probability of inclusion into the genetic sample given observables. Details on the construction of these weights are found in Appendix E.[34]

3.2 The Polygenic Score and Education

We start by replicating the basic relationship between the EA score and educational attainment found in earlier studies (Rietveld et al., 2014; Okbay et al., 2016; Lee et al., 2018). Table 2 presents estimates from regressions of years of schooling on the EA score and different control sets. The specification in Column (1) only includes the score and our basic controls. A one standard deviation increase in the EA score is associated with 0.844 more years of schooling. Note that the incremental R^2 associated with the genetic score in this regression is 0.075, indicating that variation in the score accounts for a large fraction of the variance in educational attainment.

As discussed in Section 2, the EA score could measure biological factors that enhance an individual's ability to acquire new skills or reduce the effort costs of learning. However, the score-education relationship could also reflect correlations between genetic factors and environments that promote education. For example, the genetic factors driving the score might affect parenting skills that encourage more schooling for one's children, even if these factors do not affect a child's ability to learn or acquire skill. Since the genotypes of individuals are necessarily correlated with the genotypes of their birth parents, such a scenario could generate a relationship between an individual's EA score and their educational attainment that works purely through environmental factors. To account for such factors, we would ideally like to control for parental genotypes, since the genotype of a child is randomly assigned conditional on parental genes. While we do not observe parental genes for respondents in the HRS, we can observe parental education, the phenotype most closely associated with these parental endowments.

In Column (2) of Table 2, we again regress years of schooling on the EA score but now

[34]When appropriate, we also include a cubic polynomial of the polygenic score. This is motivated by the model we develop in Appendix C, which is used to examine consequences of endogenous parental investments and measurement error and which guides our interpretation of estimates.

add separate measures for father's education and mother's education to our control set.[35] The inclusion of parental education helps to adjust for the portion of the gene-education gradient that is driven by higher investments from more educated parents who also pass their genetic material onto their children.[36] As expected, both parental education measures are positively and significantly related to a respondent's years of schooling. However, even after controlling for parental education, the EA score still exhibits a strong association with educational attainment, with an estimated coefficient of 0.614. The incremental R^2 associated with the EA score falls, but remains substantial at about 0.038. Within-family analyses in Lee et al. (2018) estimate that the associations between individual SNPs and educational attainment are, on average, approximately 40 percent smaller after accounting for family effects. In our sample, controlling for parental education reduces the estimated coefficient on the polygenic score by more than 25 percent, which accounts for a substantial fraction of the gene-environment correlation suggested by past within-family estimates. In all subsequent analyses, we control for parental education unless otherwise noted.

In Column (3), we again regress years of education on the EA score, but now add a set of categorical variables reflecting self-reported health during childhood. An extensive existing literature links childhood health to SES and labor market outcomes later in life (see Currie (2009) for a review). Indeed, we find that lower self-reported health levels (relative to the Excellent reference category) exhibit a significant negative association with educational attainment. It is worth noting that these health variables have a combined incremental R^2 of about 0.008 in this specification without the EA score (0.002 when parental education is included), which is substantially smaller than the incremental R^2 associated with the EA score itself.[37] In Column (4), we add a battery of controls measuring SES during

[35] As seen in Table 1, parental education is missing for a non-trivial number of individuals. We partially address this issue by adding separate dummy variables indicating missing values of father's and mother's education.

[36] Again, this is consistent with the results from Kong, Thorleifsson et al. (2018), who find that parental SNPs that are not passed on to children still predict their educational outcomes.

[37] In results available from the authors, we experiment with specifications adding a series of more specific controls related to health during childhood. These recall questions may be less prone to measurement error than questions about self-rated health. Additional variables include indicators for measles, mumps, chicken pox, school absences, sight problems, parental smoking, asthma, diabetes, respiratory problems, speech problems, allergies, heart conditions, ear problems, epilepsy, migraines, stomach problems, blood conditions, depression, drug use, psychological conditions, concussions, disabilities, childhood smoking, learning disabilities and other problems. When these are added to a basic regression explaining years of education (i.e., Column (1) in Table 2 but excluding the EA score), they and the self-reported health scale variables have a combined incremental R^2 of 0.079 (0.037 when parental education controls are added). Even when we control for these variables, we find that results on the relationship between EA score and educational attainment are consistent with the results in Table 2. For example, adding all of these childhood health dummies to the specification in the last column of Table 2 yields a point estimate of 0.523 for the coefficient on the EA score, which is within the 99 percent confidence interval of the estimate without these added controls (just

childhood. These include dummies for whether or not the individual's family moved due to financial stress, whether the family ever asked another family for financial help, whether or not the individual's father was ever unemployed for a significant time, and a measure for the average income of the father's occupation in the 1960 census. Adding these controls does not significantly reduce the coefficient estimate on the EA score. In Column (5), we show that our estimates are robust to the addition of dummies for the region of birth and an individual's religious affiliation. Comparing Columns (1) and (5), the entire battery of childhood socioeconomic and health controls boosts R^2 by about 0.262. The incremental R^2 of 0.034 associated with the EA score is non-trivial by comparison.[38]

Table 3 considers the relationship between the EA score and dummy variables indicating different types of highest earned degree (No Degree, Two-Year College, College, or Graduate (MA or Professional Degree)). The EA score is significantly negatively associated with having no degree and having a two-year degree, but positively associated with having a college degree or a graduate degree. Additionally, the genetic score not only predicts educational attainment, but also educational performance. Column (5) presents coefficient estimates from a specification in which the dependent variable is an indicator for whether the individual reported having to repeat a grade of schooling. The results suggest that the EA score is significantly negatively associated with the probability of repeating a grade. A one standard deviation increase in the genetic score is associated with a 4.1 percentage point reduction in the risk of ever failing a grade. Panel B of Table 3 shows that these relationships hold even when we control for parental education.[39]

Taken together, the results in Tables 2 and 3 provide support for two propositions. First, the genetic variation captured in the EA score is strongly associated with educational attainment along nearly every margin. Compared to other observables, the EA score accounts for a large fraction of the variation in educational attainment. Second, this relationship does

outside of the 95 percent confidence interval).

[38]It should be noted that many of these SES measures may be highly correlated with parental education. Thus the change in R^2 across specifications is not necessarily a good measure of the relative importance of each new set of controls, since their relationship with education may already be reflected in the relationship between parental education and own education (Gelbach, 2016). However, the aim here is not to demonstrate the relative importance of each set of controls. Rather, we are concerned with the range of explanatory power of the polygenic score as we control for additional measures of childhood circumstances. If we include the maximal set of SES controls but exclude parental education (a modified version of Column (5) in Table 2), this yields an R^2 of 0.470. Compared to the result in Column (1), this suggests an incremental R^2 of 0.217 for all SES controls when ignoring parental education. In this specification the EA score has a incremental R^2 of 0.051. Much of the explanatory power of our SES variables is being picked up by parental education. Nevertheless, the incremental predictive power of the EA score is substantial in any of these comparisons.

[39]Belsky et al. (2016) demonstrate that genetic endowments linked to completed education are associated with learning outcomes during early childhood. Using a polygenic score from an earlier GWAS, they find evidence that children with higher scores began talking earlier and, by age 7, were stronger readers.

not appear to be driven mostly by childhood environmental factors, at least those that are measurable in the HRS. After controlling for parental education, the inclusion of several controls for different aspects of childhood SES does little to attenuate the relationship between the EA score and completed education. We now take a closer look at the relationship between childhood SES and the EA score.

3.3 The Polygenic Score and Childhood SES

One aim of our subsequent analysis is to better understand how genes and the environment interact. To that end, we examine the educational outcomes of individuals with similar scores, but different childhood circumstances. While the HRS surveys individuals at older ages, it contains a set of retrospective questions in the *Demographics* file which can be used to construct variables related to the SES of an individual's household during childhood. Here, we introduce four childhood SES measures in the HRS constructed from these retrospective questions. All of the measures we construct are binary variables that take the value 1 for high childhood SES and 0 otherwise. The four variables we construct are:

1. **Father's income**: Based on respondent-provided information about father's usual occupation, we use income data from the 1960 census to impute an annual salary / work income for each father. We calculate the median for this father's income variable and classify individuals whose fathers earned above median incomes as experiencing high SES during childhood. The father's occupation measures come from the *Industry and Occupation Data*, which contain more detailed occupation codes than the items that are publicly available from HRS.

2. **Family well off**: High SES indicates respondents who reported that their family was "pretty well off financially" or "average" from birth to age 16. Low SES indicates respondents who reported that their family was "poor".

3. **Move or help**: The HRS asks separate questions about whether a respondent's family ever had to move residences or ask relatives for help due to financial reasons. Since these events are similar (capturing an extraordinary household response), we combine them into a single variable. This combination increases variation in this measure since moving or asking for help are each less frequent events.[40] High SES indicates respondents whose family never had to move or ask relatives for help for financial

[40] About 18 percent of respondent families reported having to move, and about 14 percent reported asking for help. When combined, about 25 percent had to take at least one of these actions.

reasons. Low SES indicates respondents whose families did either move or ask relatives for help.

4. **Father's employment**: High SES indicates respondents whose father never experienced a significant unemployment spell ("several months or more"). Low SES indicates respondents whose father did experience a significant unemployment spell, or those whose fathers were dead or never lived with them. Notice that this variable incorporates information on family structure since it takes the value 0 if the child is raised without a father.[41]

These SES variables have several shortcomings. For one, they are retrospective, which may lead to non-random measurement or reporting error. For example, an individual's SES during adulthood could affect how they recall or report childhood circumstances. Alternatively, perceptive individuals may be more aware of their parents' financial difficulties during childhood. If so, then any of these variables may capture unobserved skills that also lead to better economic outcomes. Moreover, the variables we use to proxy childhood SES are not exhaustive, as they do not reflect other factors affecting the level of resources available to the respondent (e.g., number of children in the household). Potential measurement problems motivate the use of several SES variables, which allows us to assess whether empirical patterns are robust across measures. Moreover, though the variable "Father's income" is based on average income data, it is unlikely to be subject to the same types of reporting error as the other variables, since the occupation question does not require an individual to make a normative judgement about their family's economic situation in childhood.

Despite possible measurement and reporting issues, we show that the SES variables exhibit consistent relationships with both educational attainment and the polygenic score. The first row of Panel A of Table 4 reports the proportion of individuals classified as high SES using each of the four measures of childhood environments. For the three variables available directly in the HRS, between 72 and 75 percent of respondents report a high-SES environment, while the corresponding number for the imputed father's income variable is 51 percent. We explore the relationship between the polygenic score and childhood environments in two ways. First, for each SES variable, Panel A reports the average fraction of respondents growing up in a high-SES environment by quartiles of the EA score distribution. For example, about 70% of individuals in the first EA quartile report that their family was either "pretty well off financially" or "average" until age 16. This fraction rises to 76% for individuals in the fourth quartile — a difference of 6 percentage points that is highly statistically significant.

[41] All results using this variable are robust to treating cases where the father is dead or never lived nearby as missing.

For all four SES variables, we find that the fraction of high-SES respondents generally rises with higher EA quartiles, and that we can reject the null hypothesis of zero difference in this fraction between the fourth and first quartiles of the EA score. The largest interquartile difference in high-SES incidence appears for the father's income variable (14 percentage points). Table 4 also presents the difference in average EA score for individuals classified as high versus low SES. Again, the largest difference appears for the father's income: individuals with a father who earned above-median occupational income have genetic scores that are on average higher by a little under one-fifth of a standard deviation.

Despite these strong gradients, much of the relationship between our SES measures and the EA score disappears after controlling for parental education. Table 4 reports interquartile differences in high SES indicators that have been residualized on our basic control set and measures of parental education. We find substantially less difference in SES environments across EA quartile groups. For the "Family well off" measure and the "Father's employment" measure, the interquartile difference becomes insignificant or only marginally significant. For the the "Father's income" and "Move or help" variables, controlling for parental education attenuates the interquartile differences by at least 50 percent. If the polygenic score exhibits similarly modest correlations with unobserved environments or investments conditional on parental education, these results provide some reason to believe that associations between the EA score and human capital outcomes are not primarily driven by gene-environment correlations. This is similar to the point made by Altonji, Elder, and Taber (2005), who study labor market returns to Catholic schooling.[42] Following this logic, adjusting for parental education bolsters the argument that differences in childhood circumstances for individuals with similar EA scores can be treated as conditionally exogenous.

While there are systematic relationships between the EA score and our SES measures, these mean differences appear to be modest compared to differences based on parental education or the respondent's own educational attainment. Not only are the mean EA scores similar across SES groups, but the distribution of the EA score is nearly identical across SES groups. As a point of reference, Panel A of Figure 3 plots the distribution of the EA score separately for individuals who did and did not complete a college degree, while Panel B does the same based on mother's education (less than twelve years versus twelve or more). Unsurprisingly, there is a substantial rightward shift in the distribution based on completing college (mean difference of 0.67), and a smaller but substantial rightward shift based on high mother's education (mean difference of 0.29). By contrast, Figure 4 plots the distribution

[42]The concern is that higher wages among individuals with Catholic schooling might be selected on unobservables so that estimated returns are spurious. They argue that if the two groups are similar on observables, they are unlikely to be so selected on unobservables as to undermine estimated returns.

of the EA score separately for high-SES and low-SES groups based on each of our four measures. In each case, we can reject the null hypothesis that the distributions are identical, but the differences in the distributions appear smaller than those based on own or parental education.[43] Indeed, the distributions across SES groups are largely overlapping. This overlap is important for subsequent analyses that test for interactions between the EA score and childhood SES and thus compare educational outcomes for individuals with similar scores, but different childhood environments. Performing such an analysis would be problematic if these distributions displayed little overlap since interactions would be identified from comparisons of individuals in the tails of each distribution (e.g., comparing high-SES individuals with unusually low EA scores against low-SES individuals with unusually high EA scores). As we can see from Figure 4, the comparison of similarly scored individuals from different SES backgrounds can be made across the distribution of the EA score. Lack of this degree of overlap is why we do not treat parental income as an additional SES measure, but instead use it as a control variable.

Panel B of Table 4 demonstrates that each of the SES measures are relevant predictors of educational attainment, with the exception of the Father's employment variable. Controlling for the EA score, our basic controls, and parental education, we find that individuals born into high-SES households are expected to complete between 0.09 and 0.71 additional years of schooling, depending on the SES measure. While controlling for parental education accounts for nearly all of the gene-SES gradient, these SES measures still contain explanatory power for education even after we condition on both parental education and the polygenic score.

In summary, Figures 2-4 along with Table 4 provide support for three propositions. First, both genetic endowments and childhood socioeconomic status appear to play important roles in driving educational attainment. Second, while our SES measures are certainly correlated with an individual's polygenic score, it appears that controlling for parental education accounts for much of the gene-environment correlation that is relevant for human capital outcomes. Third, the distribution of the polygenic score is largely similar across SES groups, which suggests we can make meaningful comparisons of individuals with similar scores, but different childhood SES.

3.4 Childhood SES and the Gene-Education Gradient

A large literature explores the extent to which conditions during childhood affect completed education and later-life outcomes (Black, Devereux, and Salvanes, 2005; Cunha and Heck-

[43] For each measure of childhood SES, the results of a Kolmogorov-Smirnov test suggest that we can reject the null hypothesis that the distributions of the EA score are equal for high and low SES groups with p-value<0.01 in all cases.

man, 2007). Of particular importance for policymakers is understanding whether changes in these conditions (e.g., increased investments in school quality) exert different influences on human capital accumulation for children with different ability endowments or accumulated skills. For example, as argued by Cunha and Heckman (2007), investments in the skills of older children from disadvantaged backgrounds might be economically inefficient if complementarities between investments and accumulated skills are sufficiently strong. Here we explore a related question — whether the effects of childhood SES on human capital accumulation differ based on levels of the endowments measured by the EA score. Our results highlight an important sign change in the interaction between childhood SES and the polygenic score in equations predicting educational attainment. We find that the relationship between the polygenic score and high school completion is weaker among individuals from high-SES backgrounds, while the relationship between the score and college completion is stronger for these individuals. Environments that promote human capital thus appear to be substitutes for genetic endowments in preventing extremely low education levels, but may complement these endowments in producing more advanced outcomes.

Figure 5 offers some motivating evidence of interactions between family SES and genetic endowments. We focus on our most predictive SES measure (Father's income) and assign each individual to a quartile of the EA score distribution and a quartile of the father's income distribution, generating 16 possible combinations of SES and EA quartile groupings. Panel A plots average rates of high school completion for each quartile combination, while Panel B reports the same exercise for rates of college completion.[44] For each quartile of father's income, higher EA quartiles are associated with a higher probability of attaining a high school degree. Moreover, within each EA score quartile, higher levels of father's income predict uniformly higher probabilities of completing high school, with sharper gradients for the first two EA score quartiles. In the lowest EA quartile, graduation probability ranges from approximately 58-84%, while in the highest it ranges from approximately 81-96%. Genetic endowments predict educational attainment, but childhood environments (as measured by father's income) also matter, especially so for individuals with lower EA scores.[45]

Panel B of Figure 5 repeats this exercise for rates of obtaining a college degree. As with high school completion, higher EA scores are associated with higher probabilities of college graduation for each quartile of father's income. Moreover, within each EA score quartile,

[44] This analysis is similar to the one in Belley and Lochner (2007), who study how parental income predicts educational attainment for individuals with similar cognitive test scores.

[45] Given that polygenic scores are not well suited to decompose the variance of a trait into genetic and environmental components, these results must be interpreted with caution. It is possible that an updated score could change the relative importance of the EA score versus father's income in predicting educational attainment.

father's income predicts college graduation, especially strongly so for the top quartile. Both genetic endowments and father's income predict higher rates of college completion. However, the differences in completion rates between above and below median income groups are much higher for individuals with high EA scores.[46] One particularly striking fact that emerges from Figure 5 is that childhood SES may overwhelm genetic endowments in predicting educational attainment. In particular, Panel B of Figure 5 shows that the college completion rate in the group formed by the lowest EA score quartile and the highest father's income quartile exceeds the corresponding fraction for individuals from the highest EA score quartile and the lowest father's income quartile, although this difference is not statistically significant.

To more formally examine whether SES moderates the relationship between the genetic score and educational attainment, we broaden our analysis to include all four SES measures and estimate regressions of the form

$$\begin{aligned} DegreeAtLeast_i^j &= X_i\beta_0 + \beta_{SES}HighSES_i + \beta_{Score}EAScore_i \\ &+ \beta_{Score^2}EAScore_i^2 + \beta_{Score^3}EAScore_i^3 \\ &+ \beta_{Int}HighSES \times EAScore_i + \epsilon_i \end{aligned} \tag{1}$$

where $DegreeAtLeast_i^j$ indicates whether individual i completed at least degree j, with $j \in \{GED,\ High\,School,\ Two\,Yr.\,College,\ College,\ Grad\}$. Here X_i contains our standard controls (a full set of birth year dummies, a male dummy, interactions between the birth year and male dummies, and the principle components from the full matrix of genetic data) along with the parental education controls. Note that we include a cubic in the EA score, since otherwise the $HighSES \times EAScore_i$ interaction could reflect non-linearities in the relationship between education and the EA score. To further control for population stratification, we also interact the principle components with $HighSES_i$ and include them as additional controls.[47] Figure 6 plots point estimates of β_{Int} and 95 percent confidence intervals for different measures of SES and for different degree measures j. Each panel presents estimates for a different SES measure. [48] The striking pattern that emerges is that there tends to be a significant negative interaction between SES and the score for completing at least low levels of education (high school equivalent or high school), but there tends to be a significant positive interaction for more advanced degrees (at least college or graduate school). To our

[46] Similar patterns emerge if we study college completion, but limit attention to individuals who graduated high school. These results are generated by the replication materials accompanying this paper.

[47] Throughout the paper, in specifications where we interact the EA score with some other moderating variable, we also include interactions between the principle components and the moderating variable.

[48] Regression results for this exercise, for the full sample and then separately for men and women, are found in Appendix B.

knowledge, this pattern has not been shown in previous literature.[49]

Moreover, the linear interactions presented in Figure 6 do not appear to be driven by outliers or by very specific ranges of the EA score. The continuous nature of the interaction is apparent from non-parametric (local polynomial) regressions describing the relationship between educational outcomes and the EA score for different SES groups, which are presented in Figures 7-8. To construct each panel of Figure 7, we regress an indicator for having at least a high school degree on a basic set of regressors: the genetic principal components, birth year dummies, a male dummy, interactions between birth year and male dummies, and controls for parental education. We then plot local polynomial regression estimates of the relationship between the EA score and these residuals separately for high- and low-SES groups. In the panels of Figure 8, we do the same, but the education outcome indicator is college degree or more. According to Figure 7, a higher polygenic score predicts higher education for both SES groups. However, the relationship is stronger for individuals who grew up in low-SES households. In contrast, Figure 8 shows that for higher educational attainment (college degree or more), the positive relationship is stronger for children who grew up in households with more resources.

3.5 Interpretation and Discussion of Mechanisms

The patterns in Figures 6-8 are consistent with human capital production functions that allow the roles of family resources and the EA score to be distinct for different outcomes at different stages of child development. Specifically, early investments in human capital (proxied by childhood family SES) may substitute for genetic endowments in preventing very low levels of educational attainment. However, these same investments could complement genetic endowments in generating higher levels of educational attainment such as college completion. It is worth mentioning that our findings on higher degrees are in line with a large literature showing that ability and investments are complements (Becker and Tomes, 1986; Cunha and Heckman, 2007; Aizer and Cunha, 2012), as well as the literature emphasizing the importance of gene-environment interactions in producing economic outcomes. However, the idea that genetic endowments and investments might be *substitutes* along some dimensions merits further exploration.

Our results suggest that some features of high-SES environments are particularly helpful

[49] If we use education controls as an additional measure of SES that we interact with the polygenic score in regressions explaining educational attainment, we obtain the same patterns as we do with the SES measures considered here. Higher parental education is associated with a steeper genetic gradient for college completion and above and with a less steep gradient for lower educational outcomes. As explained earlier, we do not present this as a main result given evidence that the distributions of the polygenic score differ substantially by mother's education, which suggests comparisons are more difficult to defend.

in preventing low-score children from dropping out of high school, and in promoting college completion among high-score children. In order for these results to have clear policy implications, it is important to understand which specific features of these environments matter for these interactions, and whether they can be manipulated by policy. For example, if father's income matters because it allows families to afford better schooling (or reside in areas with better schools), then our results might suggest that cash transfers to poor families, or investments in better quality public schooling might be particularly useful in enabling the success of high-endowment children trapped in poor environments. However, father's income could be serving as a proxy for other casaul features of the environment (e.g. parenting style) that operate independently from school quality. Without exogenous or isolated variation in these features of the environment, it becomes difficult to draw firm conclusions about the policy-relevant mechanisms that drive these interactions.

An existing literature offers some evidence on the importance of different features of high-SES environments. For example, Belley and Lochner (2007) report stronger interactions over time between AFQT scores and family income in explaining educational attainment, which suggests that borrowing constraints play an increasingly important role as tuition costs rise. As they point out, stronger interactions between family income and AFQT scores are difficult to reconcile with a "consumption value" of education, which has also been suggested as a way to explain a positive relationship between family SES and college degrees. However, credit constraints are only one possible way that family SES could alter the returns to genetic factors.[50] Interactions may also reflect physical shocks in-utero or during childhood, e.g., due to parental smoking. Environmental factors such as early-life stress could also induce changes in how genes are expressed (how they function in producing proteins), which is one example of an *epigenetic* phenomenon.[51]

The HRS contains only limited information on intermediate outcomes and specific human capital investments made by parents, so it is difficult to draw sharper conclusions about the role of household environments in our sample. However, the *Life History* file contains retrospective items that on the number of books in the respondent's household as a child, as well as whether or not the respondent went to preschool. Existing research suggests both of these investments are linked to human capital accumulation and skill formation.[52]

[50] Cohort differences are also discussed in Galindo-Rueda and Vignoles (2005), who show that the importance of ability in explaining college degree attainment declines over time, presumably because lower-ability people are more likely to be able to pay for college in comparison to earlier cohorts. See also Lovenheim and Reynolds (2011) on changes by ability and income in post-secondary choices.

[51] For example, Nestler (2012) discusses research showing that early-life conditions faced by mice can induce epigenetic effects that impact their behaviors and vulnerability to stress later in life.

[52] The number of books in a household has been used in earlier literature examining the production of cognition to proxy for parental investments in their children (see, e.g., Cunha and Heckman (2008)).

Additionally, the *Life History* file also contains a question on the number of people who lived in a respondent's household at age 10. The number of people in the household is relevant because it contains information on the number of children and other dependents in the household with claims on household resources. As noted in the literature on the quantity-quality tradeoff in fertility, poorer households may find it optimal to have more children and choose to invest less intensely in their human capital (Becker, 1960; Hotz, Klerman, and Willis, 1997). In results in Appendix B, we show that books, preschool attendance, and a lower number of individuals in the household are all associated with increased educational attainment. These measures are positively correlated with our SES measures, even after controlling for parental education. For example, regression evidence suggests that after controlling for parental education, individuals with above-median father's income are more likely to have at least one full bookcase in the household (difference of 0.059), are more likely to have attended preschool (difference of 0.049), and are less likely to have more than five people living in the household (difference of 0.067). This provides suggestive evidence that higher SES households complement higher polygenic scores through the kinds of early childhood investments that have been highlighted in existing research. However, this evidence is merely suggestive; without exogenous variation and more complete data on rearing environments and early childhood outcomes (e.g., performance at school), we cannot rule out the possibility that these measures are simply acting as proxies for different causal mechanisms (e.g., low income and binding credit constraints at college enrollment age).

3.6 Robustness and Sensitivity

Our estimates of interactions between the polygenic score and family SES are consistent with different roles for family resources depending on the level of education, which would suggest restrictions on the production function for human capital.[53] However, we cannot rule out other accounts related to measurement error or correlations between environmental factors and advantageous parental genetic endowments. For example, it could be the case that actual investment levels (which we proxy with SES) are a positive function of both observed SES and the child's genetic endowment.[54] If this is true, then SES will increasingly underestimate investment as the child's genetic endowment grows.

To help guide our interpretation of estimates, in Appendix C we develop a simple econo-

[53]In related work, Todd and Wolpin (2003) suggest that typical approaches to estimating the production of cognition may be overly restrictive. Our findings are related since they suggest that ability and investments interact in complex ways (that possibly vary by schooling level) to generate educational outcomes.

[54]Investments could rise with the child's genetic endowment because parents target resources, or because children with high endowments also have parents with high endowments who provide more resources.

metric model that incorporates several features of our setting, including: (i) using family SES to measure human capital investments introduces measurement error; (ii) investments in children are potentially affected by children's genetic endowments; (iii) these investments can also be affected by parents' genetic endowments, for example, if parents' genes lead to higher parental education, wealth or income; and (iv) children's genetic endowments are a function of their parents' genetic endowments.[55] Using the model, we show that, under a reasonable set of assumptions, such a scenario will result in bias in the magnitude but not the *sign* of gene-investment interaction effects that we estimate. Therefore, the sign change in the estimated interaction between genes and investments in low versus high educational outcomes is key. It is not a necessary condition for differences in the interaction effect, but it is a sufficient condition for the existence of such differences. We also show in Appendix C that we cannot guarantee the identification of the interaction sign if we use a more traditional measure of ability such as IQ or cognitive test scores, which may be directly affected by investments. In other words, a key benefit of using genetic data to infer how genetic endowments interact with human capital investments is that genetic endowments are fixed and therefore not simultaneously *affected* by investments, even if they are correlated with them. It is also noteworthy that our pattern of interactions is robust across a number of distinct measures of SES with different patterns of correlation with the EA score. This suggests that the interactions we find do not primarily reflect correlation between parental genetic endowments and environments.[56]

Other factors might threaten identification of the interaction term. An omitted third factor could affect education, but exhibit a different relationship with EA score for each SES group. One possibility is that our binary childhood SES measures mask differences in how household resources rise with genetic endowments. Another possibility is that there are additional genetic factors driving education that relate to the polygenic score in different ways across SES groups. In both cases, we have not identified true complementarities, but instead have captured omitted factors. Finally, there may also be classification error that differs by group if, for example, individuals with lower polygenic scores are more likely to

[55] As mentioned earlier when we discuss our standard control set, the model motivates why we allow for heteroskedastic error terms and include a polynomial in the polygenic score for all specifications, which helps to control for measurement error.

[56] Another possibility is that the interactions that we estimate arise from non-linearities in the human capital production function. Suppose that the genetic score is related to education in a non-linear fashion, and that SES is correlated with the genetic score. Then we could estimate significant score-SES interactions that have nothing to do with differences in the production function across SES groups. That is, an interaction between the score and observed SES may simply reflect an underlying non-linear relationship between the score and education. As discussed earlier, we control for non-linearities through a cubic in the EA score for all specifications examining the interaction between the EA score and childhood SES to explain educational attainment. We thank Jonathan Beauchamp for pointing out this possibility.

mis-classify their childhood SES. The ideal experiment to test for these effects would involve a random assignment of resources that can be manipulated by policy (e.g. household income) to individuals with different genetic scores.

While we cannot rule out the threats to identification rooted in selection on unobservables, the distributions of the polygenic score by SES group plotted in Figure 4, in particular the substantial overlap, help to allay some concerns. The reasoning is similar to that in Altonji, Elder, and Taber (2005). The plots demonstrate that when we divide the sample by childhood SES, the resulting groups are quite similar with regard to an important and relevant observed source of heterogeneity. Similar polygenic scores across groups provide some support for the assumption that individuals are similar on unobserved factors as well, i.e., that estimated differences in returns to genetic endowments by childhood SES are not the result of selection on unobservables.[57]

We also acknowledge that our conclusions here are based on a fairly large number of specifications that span four different SES measures and five different educational outcomes. This raises the possibility that our results could be false positives that emerge from multiple hypothesis testing. In Appendix E, we adjust the p-values associated with our main hypothesis tests to account for multiple comparisons. We continue to have strong statistical evidence for multiple SES-EA score interactions even after applying these corrections.

4 Genes and Labor Outcomes

Results from the previous section suggest that low-SES environments reduce the returns to genetic endowments by lowering the probability of college attendance. This is particularly important in light of the substantial rise in the earnings premium for a college degree over the last several decades. However, earnings depend not only on completed education, but also on the returns to endowments conditional on education. High-score individuals who are shut out of college due to childhood poverty might still receive an earnings premium if the genetic endowments measured by the EA score are also associated with skills valued in the labor market. This motivates an analysis of the relationship between the score and earnings conditional on education.

The questions we ask here are related to a longstanding literature on the returns to ability. At least since Becker and Chiswick (1966), labor economists have been concerned with *ability*

[57] In results available from the authors, we assess robustness if we restrict attention to individuals who are not in the tails, i.e., if we rerun regressions dropping individuals with EA scores in the top or bottom 5 percent. We continue to find positive and significant interactions between SES and the EA score in predicting college completion. However, we note that with this restriction many of the interaction terms become insignificant in the specifications predicting high school completion.

bias in estimating the relationship between schooling and various economic outcomes. If the unobserved factors that promote education also independently predict labor market success, then estimates of the return to schooling will be biased upwards. This concern not only raises an econometric point; it also poses fundamental questions about the structure of heterogeneity in labor market decisions and outcomes. How and to what extent do the characteristics or traits that promote education also affect earnings over the the life-cycle? Observing the EA score thus also allows us to make some progress on this larger question, demonstrating how previously unobserved factors might not only drive education, but also several other outcomes conditional on education.

4.1 The EA Score and Earnings

We begin by describing the relationship between the EA score and earnings over the life-cycle. Panel A of Figure 9 plots the relationship between age and the unconditional average earnings of men in our sample separately by terciles of the EA score. Each tercile group exhibits a classic concave age-earnings profile, with earnings rising until approximately age 55, then falling afterwards. At every age, earnings are higher for individuals in higher EA terciles. To explore whether this pattern also holds conditional on education, we next regress earnings on controls for own and parental education and plot the residuals separately by EA tercile.[58] Residual earnings diverge considerably as respondents age, and for most ages in the range 40-60 we can reject the null hypothesis that residual earnings are equal across the top and bottom terciles. Together both panels suggest that the EA score predicts higher earnings, this gradient is not fully explained by educational attainment, and it becomes larger as individuals age. We note that this pattern of divergence would not be fully captured by a standard fixed effects model, since fixed effects do not change over time by construction. This illustrates how observable measures, such as the EA score, can help us to better understand the structure of heterogeneity in labor outcomes. These patterns are also consistent with findings of Altonji and Pierret (2001), who demonstrate that measures of labor market ability that are presumably difficult to observe, like the AFQT, become better predictors of wages as individuals age and accumulate more experience.[59]

[58] Specifically, we include our standard controls, years of father's and mother's education separately, dummies for missing values of father's and mother's education, years of own education, and separate dummies for each possible completed degree.

[59] Altonji and Pierret (2001) attribute this empirical pattern to the dynamics of employer learning. Early in an individual's work history, firms make wage offers conditional on easily observable characteristics such as educational attainment that are useful but are not sufficient to describe a worker's true productivity. Measures like the AFQT might better capture the worker characteristics that are relevant for productivity, but firms typically have a hard time observing these proxies. However, as workers age and accumulate experience, employers learn more about worker characteristics. Consequently, as workers age, the correlation

Table 5 presents more formal estimates of the relationship between the EA score and log earnings. Here we restrict the sample to all person-year observations for men aged 25-64 with at least \$10,000 of annual earnings.[60] Standard errors are clustered at the person level. Panel A contains our baseline specification, which regresses log earnings on the EA score and a controls set that consists of the principal components, as well as dummy variables for age, year, and birth year. As seen in Column (1) of Panel A, without any controls for own education a one standard deviation increase in the EA score is associated with an increase in log earnings of 0.079. In Column (2) we add controls for own education (years of schooling and a full set of degree dummy variables) and parental education. Controlling for education and parental background, we estimate a coefficient on the EA score of 0.032, which remains highly significant. Thus far, we have assumed that the returns to the EA score would be the same regardless of an individual's level of education. However, returns to the EA score might plausibly differ based on an individual's level of completed schooling. For example, we might expect there to be larger returns to genetic endowments if formal education is a productive complement with ability in generating productive skills. Consequently, we explore whether there is any interaction between the genetic score and having at least a college degree. The results in Column (3) do not allow us to reject the null hypothesis that there is no additional return for those with a college degree.[61] However, we do note in robustness exercises that there appears to be a larger return for college graduates when we consider self-reported wages in the HRS as the dependent variable.[62] Importantly, we find no evidence that high-EA score individuals without a college degree experience sufficient returns on their endowments to compensate for the lack of a degree. Finally, in Column (4) we restrict the sample to individuals aged 40-64 and re-estimate our basic specification from Column (2). We find a larger association between the EA score and earnings conditional on education for this older sample (0.041 versus 0.032), consistent with the pattern suggested by Panel B of Figure 9.

In Panel B, we examine whether the association between the score and earnings has evolved over time or across cohort groups. This is motivated by the large literature in labor

between wages and these proxies for hard-to-observe ability should increase.

[60]The threshold of \$10,000 is arbitrary, but this is chosen to restrict the sample as much as possible to full time workers and exclude those who are marginally attached the labor force.

[61]To control for possible population stratification, we also include interaction terms between the principal components and the indicator for a college degree.

[62]In Appendix B, we also show that there appear to be substantially larger *wage* returns to the EA score for individuals with a college degree. This difference is statistically significant when estimating an a wage equation using self-reported wage data from the HRS. When we restrict the SSA earnings data to match the years and ages of the HRS sample, we find point estimates that suggest a larger return to the EA score among college graduates, although the difference in returns between those with and without a college degree is not statistically significant.

economics demonstrating a rise in the return to skill and an increase in residual income inequality over the last several decades (Lemieux, 2006; Autor, Katz, and Kearney, 2008; Acemoglu and Autor, 2011; Lochner and Shin, 2014). In Column (1), we interact the score with an indicator for years after 1980, when massive technological changes emerged in the work place, such as the advent of computers. We find that the coefficient on the EA score goes to zero while the interaction between the EA score and post-1980 is large and significant (0.077).[63] However, it could be that the higher returns to the EA score after 1980 simply reflect the post-1980 increases in the college wage premium. In Column (2), we include a college degree dummy interacted with the post-1980 dummy to account for this. Indeed, we find an increase of 0.276 in the log-earnings premium associated with a college degree after 1980. Adding this interaction causes a reduction in the coefficient on the EA score post-1980 interaction to 0.039, but it remains highly statistically significant. Results using the post-1980 dummy could reflect either a time or cohort interaction, since the correlation coefficient between year of birth and calendar year in our earnings sample is over 0.60. In Column (3), we instead interact the genetic score with an indicator for being born after 1942 (median birth year in the wage sample). The coefficient on the interaction is close to zero. In Column (4), we add an interaction between college and education being born after 1942 to the specification in Column (3) and find a substantial interaction between post-1942 birth cohorts and having a college degree (0.152), but a small and insignificant interaction between the EA score and post-1942 birth cohorts. In Column (5), we include all interaction terms from the specifications in Columns (2) and (4). We only find statistically significant interactions between the EA score and post-1980 years, and between having a college degree and post-1980 years. This suggests that something about the labor market changed after 1980 to alter the returns that individuals experienced to the characteristics summarized by the EA score, regardless of their birth cohort.[64]

One limitation of the SSA data is that they do not contain information on hours worked, preventing an analysis of wages. This raises the possibility that our results on earnings could be driven by differences in labor supply instead of changes in productivity. Indeed, in Appendix B, we find that men with higher values of the EA score are more likely to work, and are less likely to retire in a given year. Here the self-reported earnings data in

[63] To control for population stratification, we always include interactions between the principle components and the "Year > 1980" and "Birth Year > 1942" indicators whenever these binary variables are interacted with the EA score in Panel B of Table 5.

[64] One potential confounding factor is the sharp drop in the extent of top-coding patterns in the SSA data that occurred in the late 1970s and early 1980s. As described in Appendix B, the divergence in earnings between EA terciles appears to happen continuously after 1980 at a time when the top-coding scheme was relatively stable. This suggests that the post-1980 rise in the association between the EA score and earnings is unlikely to be solely due to changes in top-coding.

the HRS are useful, even though they are limited to observations on older men after 1990. In Appendix B, we find that the EA score exhibits similar associations with both the log of self-reported earnings and the log of self-reported wages in the HRS, suggesting that our earnings results are unlikely to be driven by labor supply differences.

Our earnings results suggest two key points. First, the EA score measures individual traits or characteristics that earn a premium in the labor market, above and beyond completed schooling. Second, this additional return to the EA score appears to have grown over time, and after 1980 in particular. This timing is significant because a large literature documents not only a rise in the returns to schooling beyond this point, but a rise in the returns to observable measures typically associated with labor market ability. Murnane, Willett, and Levy (1995) find that the returns to cognitive skills (measured by math test scores) were larger in the 1980s compared to the 1970s for young workers. Similarly, Gould (2002) provides evidence of a rise in the returns to intelligence based on evidence from cognitive tests scores.[65]

4.2 Genes, Job Tasks and Skill-Biased Technological Change

The empirical patterns demonstrated in the previous section are consistent with the ongoing rise in the returns to skill. This phenomenon is often explained by the complementarity between certain skills or abilities and the introduction of new technologies during this time period (Acemoglu, 1998). Some individuals may have a greater capacity for learning how to use new technologies, either because of genetic endowments or because of past human capital investments. Such individuals may find it easier to adapt to technological shocks and use them to enhance their productivity in the workplace. If the EA score captures such an ability to learn new skills, then the rising return to genetic endowments may be a consequence of skill-biased technological change (SBTC). This suggests an interesting extension to the idea of gene-environment interactions, which are often thought of as pertaining to household environments or other investments made in human capital. Our results suggest that another environmental factor is the state of technology, which can unexpectedly shift over time, making some genetic endowments more or less productive in ways that are difficult to anticipate and plan for.

To examine whether SBTC can help to explain wage returns to ability across birth cohorts, we next consider how the EA score relates to job tasks. The literature on SBTC has implicated computerization as an important driver of rising returns to cognitive skills. In a

[65] Further contributions to this literature include Juhn, Murphy, and Pierce (1993), Taber (2001) and Tobias (2003).

review of the literature Katz and Autor (1999) discuss many reasons why increased access to computers shifts the demand for skilled labor. For example, it could be the case that skilled workers are "more flexible and facilitate the adoption of new technologies so that all technological change increases the relative demand for more-skilled labor," (p. 1535). Alternately, more skilled workers might be able to work more creatively with available information.

In an influential study, Autor, Levy, and Murnane (2003) link computerization and SBTC to the tasks that workers perform on the job. Specifically, Autor, Levy, and Murnane (2003) argue that computerization should substitute for the labor of workers with jobs that involve repetitive tasks that follow explicit rules or patterns (routine tasks). Conversely, computerization should complement the labor of workers who carry out non routine tasks that involve "problem-solving and complex communication activities." Autor, Levy, and Murnane (2003) use the Department of Labor's *Dictionary of Occupational Titles* to measure the intensity of five relevant tasks types: (i) non-routine analytic (use of math); (ii) non-routine interactive (direction, control and planning); (iii) routine cognitive (set limits, standards and tolerances); (iv) routine manual tasks (finger dexterity); and (v) non-routine manual (eye, hand and foot coordination). Examining patterns within education, occupation, and industry groups, Autor, Levy, and Murnane (2003) indeed find that computerization has been associated with a rise in non-routine cognitive tasks, and a reduction in routine cognitive and routine manual tasks.

Data from Autor, Levy, and Murnane (2003) provide measures of how intensely every Census occupation uses the five job tasks listed above.[66] Although the public release of the HRS contains masked aggregated occupation codes, we use the detailed occupation codes available in the restricted *Industry and Occupation Data* file. Since a given task intensity has no natural interpretation, we standardize each intensity to have a mean of zero and a standard deviation of one. Table 6 presents estimates of the relationship between the genetic score and the task intensity for the occupation. The specification here includes all person-year observations for men between the ages of 50-64 with non-missing occupation data. Panel A regresses the job task intensities on the principal components, and a full set of age, year, and birth year dummies. Importantly, we do not include controls for parental or own education in these specifications.

The results in Panel A suggest that the EA score is positively associated with both non-routine analytic and interactive tasks, and negatively associated with routine tasks. We find no evidence of an association with non-routine manual tasks. These results are consistent

[66] Data on the task intensities associated with each occupation can be found on David Autor's website: `http://economics.mit.edu/faculty/dautor/data/autlevmurn03`. The Autor, Levy, and Murnane (2003) task intensity measurements that we use are based on the 1991 *Dictionary of Occupational Titles* associated with male workers.

with the proposition that the EA score is associated with job tasks that were complemented by computerization. However, the associations in Panel A may reflect the associations between completed schooling and occupation. In Panel B, we repeat the specifications in Panel A but now control for parental and own education. After controlling for education, we still find a positive association between the EA score and the non-routine analytic tasks. A one-standard-deviation increase in the EA score is associated with a 0.073 standard deviation increase in non-routine analytic task intensity, and a 0.055 standard deviation increase in non-routine interactive task intensity. We find no statistically significant associations between the EA score and other task intensities after controlling for education.

Given the results present in Table 6, we explore whether we observe a similar relationship between the EA score and non-routine analytic tasks across education groups. In particular, Figure 10, plots the EA score against the standardized non-routine analytic task intensity for respondents with and without a college degree. For either education group, individuals with higher scores are more likely to be in occupations where they perform more sophisticated tasks. This may help explain patterns shown in Figure 9, which shows that higher scores predict higher earnings after adjusting for education. However, these figures also highlight one source of the college premium. Across the entire EA score distribution, individuals without a college degree are predicted to have a lower average intensity of this task than individuals with a college degree.

The results presented in this section add some nuance to our conclusions regarding genetic endowments and earnings. The gene-earnings gradient only appears after 1980 in the SSA data. This pattern appears quite consistent with complementarities between technological change and genetic proclivity for learning. This account is bolstered by the positive association between the score and non-routine cognitive job tasks. Yet, while individuals with high polygenic scores and across education groups profit from new technologies, the college premium remains massive. Importantly, the genetic gradients in both earnings and job tasks are roughly similar for individuals with and without a college degree. This suggests that high-EA individuals without a college degree do not find ways to easily sort into jobs with tasks that heavily complement new technologies. Genetic endowments do not compensate for a lack of a college degree in the labor market. Coupled with our earlier finding that college completion for individuals with similar scores depends in large part on childhood SES (e.g., father's income), results in this section suggest that there may be unrealized human potential in the economy.[67]

[67] In Appendix B, we conduct a similar analysis to the one used to generate Figure 5, relating quartiles of father's income and of the EA score to the average annual earnings in adulthood. The aim is to assess whether education differences predicted by interactions between the EA score and father's income shown in Figure 5 translate to earnings differences. We find that earnings for individuals in the lowest EA score

5 Discussion

Recent breakthroughs in behavioral genetics — most notably the research presented in Rietveld et al. (2013), Okbay et al. (2016) and Lee et al. (2018) — allow researchers to observe genetic endowments that robustly explain educational attainment. Using HRS data, we show that up to 7.4 percent of the variation in educational attainment is explained by the genetic index presented in Lee et al. (2018) (the EA score). Childhood SES appears to moderate the relationship between this index and various levels of educational attainment — particularly obtaining a college degree. The endowments measured by this index also predict earnings, job tasks, and labor supply later in life. Finally, we provide novel evidence that the wage premium associated with the genetic index has risen over time. We argue that structural changes in the economy, and skill biased technological change in particular, may have contributed to a rise in the genetic gradient.

An important caveat to our results is that the genetic endowments measured by the EA score are not exogenously assigned. Individuals with higher values of the EA score necessarily have birth parents with high values of the EA score, making it difficult to determine how much of the associations we estimate arise from the biological traits linked to these genetic markers, or to the positive environments provided by their parents. Nevertheless, results from previous studies using within-family designs suggest that the majority of the associations used to construct the score remain even after controlling for family fixed effects. Controlling for parental education seems to account for much of this gene-environment correlation. Nevertheless, the associations we report conditional on education might still reflect unmeasured investments or other features of the environment that are not observed in the HRS data.

Our results suggest several interesting avenues for future research. Observed genetic heterogeneity could be incorporated into structural models that are often devised for use in *ex ante* policy evaluation. Such models could be used to explore long-run dynamics, such as inter-generational mobility, or to better understand how education policy can reduce inequality. The structure of heterogeneity assumed in these models is often tremendously important in driving predictions about labor market dynamics. For example, in a seminal contribution to the field, Keane and Wolpin (1997) suggest that 70 percent of the variability

quartile but the highest father's income quartile have average annual earnings that are similar to individuals in the lowest father's income quartile and the highest EA score quartile. We also find some inconclusive results on how the SES-earnings gradient changes across EA score quartiles. Examining differences in average earnings between the fourth and second quartiles of father's income suggests that the SES-earnings gradient is substantially higher for individuals in the top three EA score quartiles compared to the bottom quartile. However, there is no clear pattern when examining differences in average earnings between the fourth and first quartiles of father's income.

in the career paths of young men is driven by heterogeneity in unobserved factors (at age 16). When building these kinds of models, researchers face a large number of choices about how to model heterogeneity — from picking which parameters to make random, to determining the structure of correlation between unobservables. The results presented here may offer some restrictions on the structure of heterogeneity in these models. For example, our estimates offer some empirical benchmarks on how the unobservable genetic factors that drive education relate to wages and wealth, conditional on education. Our findings also point to possible differences in the education production function for high school versus college completion.

Another extension of the literature would seek to combine the polygenic score studied here with more exogenous measures of childhood SES. We believe that plausible assumptions allow us to at least sign the interaction between genetic endowments and childhood SES, even though these may be simultaneously determined by parental genes. Nevertheless, more robust inferences could be made with access to randomly assigned childhood circumstances or investments. Indeed, in any *ex post* evaluation of an existing policy, the genetic score can be used to detect the presence of heterogeneous effects by genetic endowments.

Another important task is to better understand the mechanisms that link the polygenic score studied here and economic outcomes. In ongoing work, we try to understand the relationship between the score, beliefs formation and the ways in which people make health and financial decisions. If the genetic underpinnings of education function through their impact on how people process new information, then this might offer clues as to how policies could be designed to better maximize the potential of individuals with disparate ability endowments. Such insights might ultimately guide the design of school curricula or the content of interventions such as job-training programs.

More broadly, a recurring theme in our empirical results is that individuals with similar abilities, but born into different socioeconomic circumstances, face diverging economic outcomes. These findings suggest an important role for policies that invest in poor children and, more generally, provide some support that such investments could mitigate inefficiently low investments in human capital (Heckman and Masterov, 2007). Our findings on wasted potential complement mounting evidence from a variety of fields suggesting the misallocation or squandering of human resources. Researchers have reached this conclusion in different ways. For example, Hsieh et al. (2013) show evidence that innate talent, especially among blacks and women, is likely misallocated across occupations, and highlight the implications of misallocation for economic growth in the United States. In another study, Chetty, Henden, and Katz (2016) demonstrate that randomly assigned vouchers that move children from high-poverty to less-poor neighborhoods can improve labor market performance in the long run. This suggests that policy-relevant factors affect how well a child with a given set of endowments will eventually perform.

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6 Tables and Figures

Table 1: Summary Statistics - HRS Sample

Variable	Mean	Std.	N
Male	0.417	0.493	8537
Birth Year:			
< 1930	0.227	0.419	8537
1930-1934	0.152	0.359	8537
1935-1939	0.183	0.387	8537
1940-1944	0.161	0.367	8537
1945-1949	0.126	0.332	8537
1950-1954	0.151	0.358	8537
Degree:			
Education (Years)	13.161	2.538	8537
None	0.129	0.335	8512
GED	0.045	0.207	8512
High School	0.529	0.499	8512
College (2 year)	0.05	0.219	8512
College (4 year)	0.147	0.354	8512
Masters	0.077	0.267	8512
Advanced	0.023	0.148	8512
Redo Grade	0.14	0.347	8166
Parents' Educ. (Years)			
Father	10.229	3.593	6711
Mother	10.672	3.017	6993
SSA Earnings (96,721 person-year obs.)			
Mean	59,180		
Std. Dev.	32,851		
25^{th} percentile	34,173		
50^{th} percentile	55,295		
75^{th} percentile	75,005		
Num. Respondents	3,140		

Variable	Mean	Std.	N
Father's Income	28.588	10.348	6773
Family SES (Childhood)			
Well Off	0.067	0.25	8537
Average	0.645	0.478	8537
Poor	0.273	0.446	8537
Varied	0.013	0.114	8537
Missing	0.001	0.034	8537
Refused	0.000	0.019	8537
Family Moved (Childhood)			
Yes	0.180	0.384	8537
No	0.816	0.387	8537
Missing	0.004	0.062	8537
Refused	0.000	0.015	8537
Fam. Asked for Help (Childhood)			
Yes	0.134	0.341	8537
No	0.851	0.356	8537
Missing	0.015	0.12	8537
Refused	0.000	0.015	8537
Father Lost Job (Childhood)			
Yes	0.204	0.403	8537
No	0.728	0.445	8537
Never Worked	0.006	0.075	8537
Never There	0.056	0.229	8537
Missing	0.007	0.084	8537
Refused	0.000	0.015	8537
Health as Child			
Excellent	0.545	0.498	8537
Very Good	0.256	0.436	8537
Good	0.143	0.35	8537
Fair	0.044	0.206	8537
Poor	0.012	0.108	8537
Missing	0	0.015	8537

Summary statistics for the primary analytic sample, which consists of 8,537 individuals from the HRS. The sample is limited to individuals of European ancestry genotyped in the 2006 and 2008 waves. The earnings data consist of 96,721 person-year observations for 3,140 men from our sample with non-missing earnings data from the Social Security Administration Master Earnings File (MEF). These summary statistics are calculated without sampling weights. Missing values for the socioeconomic status variables include the responses "Don't Know," as well as cases where a response was not ascertained or the question was not asked.

Table 2: Polygenic Score and Educational Attainment

	(1)	(2)	(3)	(4)	(5)
EA Score	0.844***	0.614***	0.610***	0.589***	0.587***
	(0.046)	(0.043)	(0.043)	(0.045)	(0.032)
Father Educ		0.147***	0.144***	0.107***	0.109***
		(0.013)	(0.013)	(0.016)	(0.013)
Mother Educ		0.172***	0.170***	0.149***	0.150***
		(0.016)	(0.016)	(0.016)	(0.015)
Child Health: Very Good			-0.141	-0.100	-0.128*
			(0.126)	(0.116)	(0.070)
Child Health: Good			-0.259**	-0.190	-0.422***
			(0.127)	(0.123)	(0.090)
Child Health: Fair			-0.197	-0.114	-0.407***
			(0.168)	(0.175)	(0.145)
Child Health: Poor			-0.651	-0.549	-0.853
			(0.579)	(0.572)	(0.573)
Child Health: Missing			1.561***	1.054	1.995
			(0.415)	(1.159)	(1.243)
Obs.	8537	8537	8537	8537	8537
R^2	0.253	0.361	0.363	0.380	0.515
Child SES Measures	N	N	N	Y	Y
Child Region	N	N	N	N	Y
Religion	N	N	N	N	Y
Incr. R^2, EA score	0.075	0.038	0.037	0.034	0.034

Regressions relating educational attainment (years) to the EA score. All regressions include a full set of dummy variables for birth year, a male dummy, and a full set of interactions between the birth year and gender dummies. All specifications include the first 10 principal components of the full matrix of genetic data as controls. Some specifications include controls for parental education, childhood health, childhood SES measures, region during childhood and religion, as indicated. The last row reports the incremental R^2 of the EA Score.

Table 3: Polygenic Score and Categorical Education Outcomes

	(1)	(2)	(3)	(4)	(5)
Dep Var.	No Degree	Two-Year Coll.	College	Graduate	Redo Grade
Panel A:					
EA Score	-0.068***	-0.008**	0.069***	0.063***	-0.041***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)
Obs.	8512	8512	8512	8512	8166
R^2	0.201	0.046	0.082	0.094	0.085
Panel B:					
EA Score	-0.050***	-0.010***	0.051***	0.050***	-0.030***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)
Father Educ	-0.008***	-0.000	0.013***	0.011***	-0.008***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Mother Educ	-0.016***	0.004**	0.014***	0.008***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Obs.	8512	8512	8512	8512	8166
R^2	0.251	0.050	0.120	0.122	0.098

Regressions relating educational attainment categories or the probability of repeating a grade to the EA score. Specifications in Panel A do not include parental education. Specifications in Panel B include parental education. All regressions include a full set of dummy variables for birth year, a male dummy and a full set of interactions between the birth year and gender dummies. Additionally, every specification includes the first 10 principle components of the full matrix of genetic data.

Table 4: Childhood SES Measures and Education

	(1)	(2)	(3)	(4)
SES Measure:	Father Inc.	Fam. Well Off	Never Move or Ask.	Father Emp.
Panel A: EA Score and Four Measures of High Family SES				
Full Sample Average	0.510	0.721	0.746	0.741
EA Score Quartile 1:	0.432	0.699	0.716	0.713
EA Score Quartile 2:	0.487	0.705	0.741	0.751
EA Score Quartile 3:	0.540	0.719	0.749	0.717
EA Score Quartile 4:	0.572	0.761	0.776	0.780
Q4−Q1	0.139	0.061	0.060	0.067
p-value	<0.001	0.014	0.015	0.002
Q4−Q1 (Residuals)	0.064	0.004	0.030	0.037
p-value	0.007	0.833	0.174	0.072
Δ EA Score for				
High vs Low SES	0.196	0.122	0.143	0.104
p-value	<0.0001	<0.0001	<0.0001	<0.0001
Panel B: Dep. Var - Education				
High SES	0.708***	0.592***	0.363**	0.092
	(0.127)	(0.129)	(0.153)	(0.123)
EA Score	0.597***	0.610***	0.609***	0.613***
	(0.047)	(0.043)	(0.045)	(0.043)
Obs.	6773	8412	8385	8427
R^2	0.398	0.370	0.364	0.361

Specifications relating four measures of childhood SES to education and EA score. Panel A shows how the EA score relates to family SES. The first row shows the proportion in the sample indicating high SES for each measure among those who report the measure. The following rows show the proportion indicating high SES for each measure within each EA score quartile. We also report p-values for differences between the first and fourth quartiles. We also repeat this exercise after residualizing the SES measures on our basic controls and parental education measures. For the residualized measures, we only report differences between the first and fourth quartiles of the EA score distribution, along with the associated p-values for these differences. Panel B contains coefficients on measures of high SES and EA score in regressions explaining educational attainment (years). Regressions also include a full set of dummy variables for birth year, a male dummy and a full set of interactions between the birth year and gender dummies. Additionally, every specification includes the first 10 principle components of the full matrix of genetic data, and controls for parental education.

Table 5: Polygenic Score and Earnings

Panel A: Log Earnings Basic Specifications	(1)	(2)	(3)	(4)	
EA Score	0.079***	0.032***	0.025**	0.041***	
	(0.009)	(0.009)	(0.010)	(0.011)	
EA Score x College			0.016		
			(0.020)		
Obs.	96721	96721	96510	57469	
R^2	0.143	0.189	0.192	0.150	
Age Group	25-64	25-64	25-64	40-64	
Period	All Years	All Years	All Years	All Years	
Educ. Controls	N	Y	Y	Y	
Parent Controls	N	Y	Y	Y	

Panel B: Log Earnings By Time and Cohorts	(1)	(2)	(3)	(4)	(5)
EA Score	-0.010	0.009	0.018**	0.026***	0.011
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
EA Score x Post 1980	0.077***	0.039***			0.043***
	(0.013)	(0.013)			(0.010)
EA Score x BY > 1942			0.031*	0.009	-0.010
			(0.019)	(0.019)	(0.019)
College x Post 1980		0.276***			0.256***
		(0.031)			(0.024)
College x BY > 1942				0.152***	0.041
				(0.045)	(0.044)
Obs.	96721	96510	96721	96510	96510
R^2	0.194	0.204	0.192	0.196	0.206
Ed. Groups	All	All	All	All	All
Period	All Years	All Years	All Years	All Years	All Years
Educ. Controls	Y	Y	Y	Y	Y
Parent Controls	Y	Y	Y	Y	Y

Regressions relating the EA score to log earnings. In the first three columns of Panel A, we restrict the sample to earnings records for men between the ages of 25 and 64 over the years 1951-2013. We further restrict the sample to person-years in which the respondent earned more than $10,000 in real 2010 dollars. In Column (4), the sample is narrowed to cover person-years in which respondents are aged between 40 and 64. The specifications in Panel B cover ages 25-64 and years 1951-2013. The dependent variable is the log of real earnings. All regressions include the first 10 principle components of the full matrix of genetic data along with a full set of dummy variables for birth year, calendar year and age. As noted in the table, some specifications include controls for parental education (years of paternal and maternal education and dummies indicating missing values for each) and own education (years of schooling and a full set of completed degree dummies). Standard errors in all specifications are clustered at the person level.

Table 6: Polygenic Score and Standardized Job Tasks

Panel A:	(1)	(2)	(3)	(4)	(5)
Dep Var.	Non-Routine Analytic	Non-Routine Interactive	Routine Cognitive	Routine Manual	Non-Routine Manual
EA Score	0.248***	0.185***	-0.080***	-0.147***	-0.021
	(0.024)	(0.022)	(0.023)	(0.022)	(0.025)
Obs.	9948	9948	9948	9948	9948
R^2	0.104	0.068	0.028	0.052	0.032
Educ. Controls	N	N	N	N	N
Panel B:	(1)	(2)	(3)	(4)	(5)
Dep Var.	Non-Routine Analytic	Non-Routine Interactive	Routine Cognitive	Routine Manual	Non-Routine Manual
EA Score	0.073***	0.055**	0.021	-0.009	0.026
	(0.023)	(0.022)	(0.023)	(0.022)	(0.026)
Obs.	9948	9948	9948	9948	9948
R^2	0.286	0.173	0.094	0.160	0.048
Educ. Controls	Y	Y	Y	Y	Y

Regressions relating EA score to job tasks. In both panels, the dependent variable is job task intensity, as constructed by Autor, Levy, and Murnane (2003). We standardize each task measure by subtracting its mean and dividing by its standard deviation within our sample. All regressions include the first 10 principle components of the full matrix of genetic data, as well as a full set of dummies for birth year, calendar year and age. Specifications in Panel B include controls for parental education (years of paternal and maternal education and dummies indicating missing values for each) and own education (years of schooling and a full set of completed degree dummies). In all columns the sample is restricted to men between the ages of 50 and 64. Standard errors are clustered at the person level.

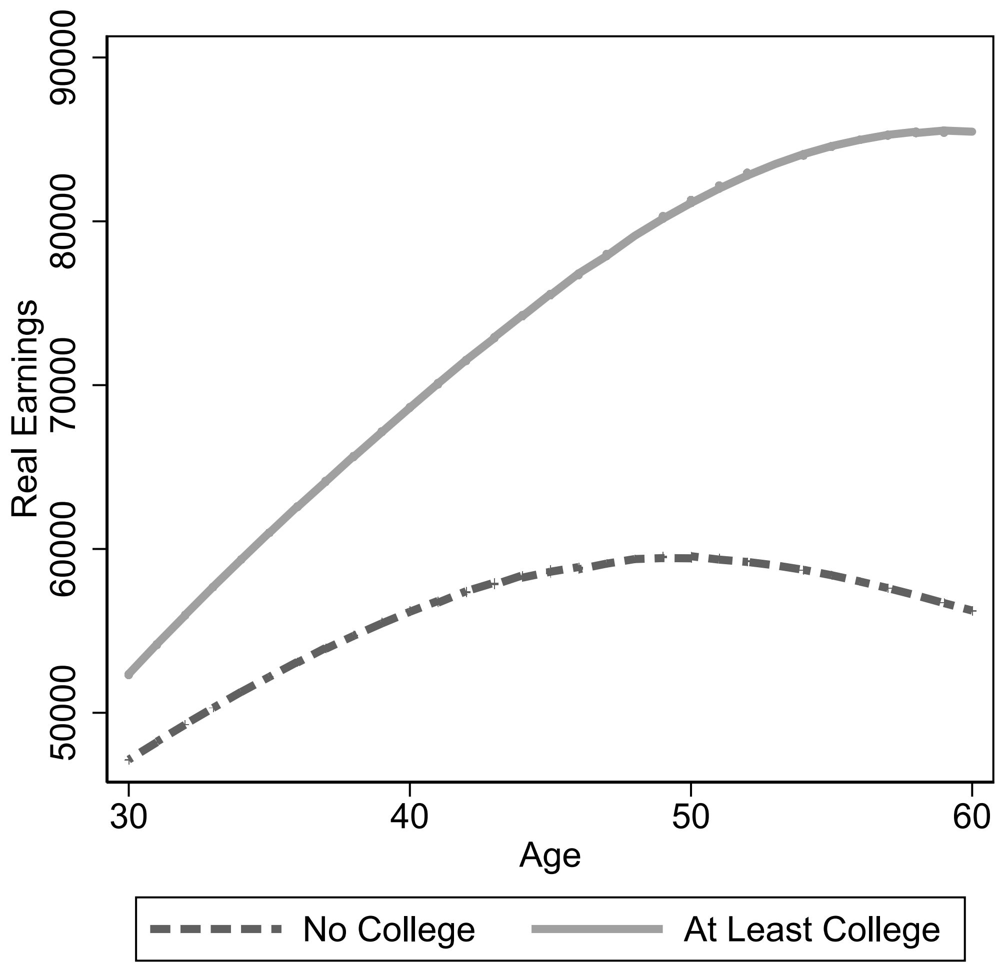


Figure 1: Age-Earnings Profiles by Education Group. Non-parametric (lowess) estimation relating age to earnings separately for those with and without a college degree.

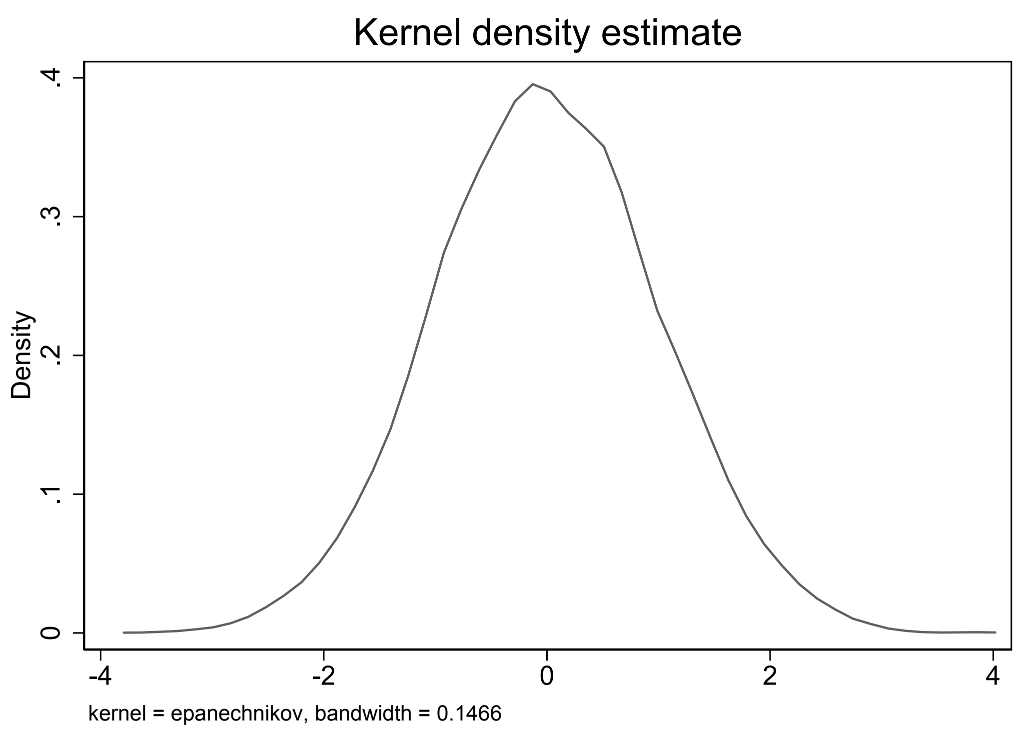
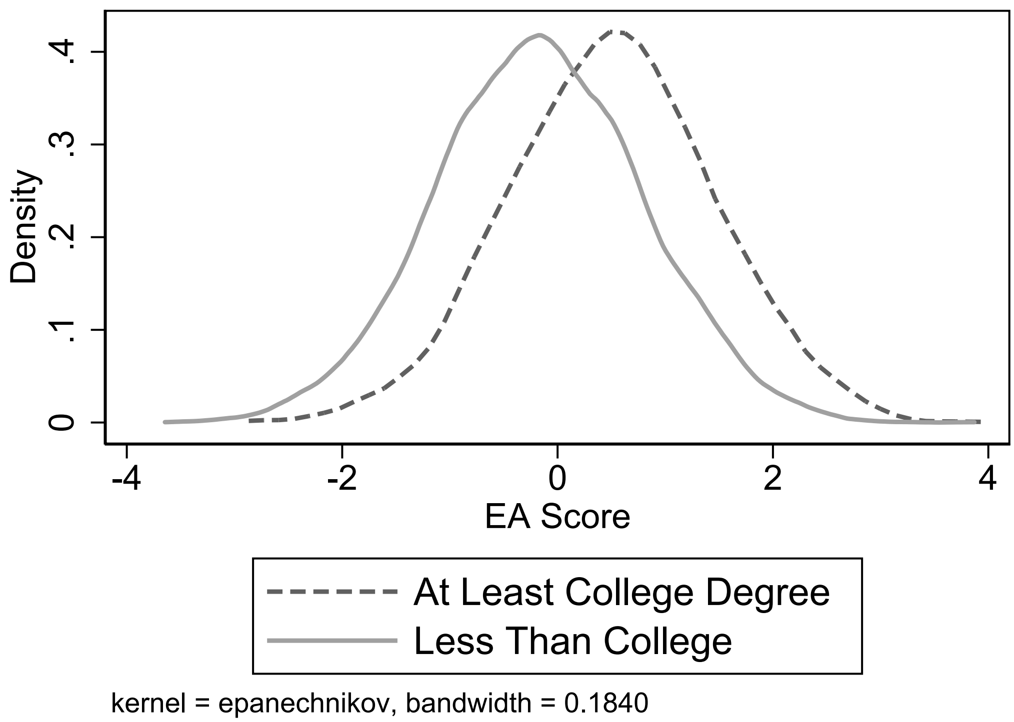
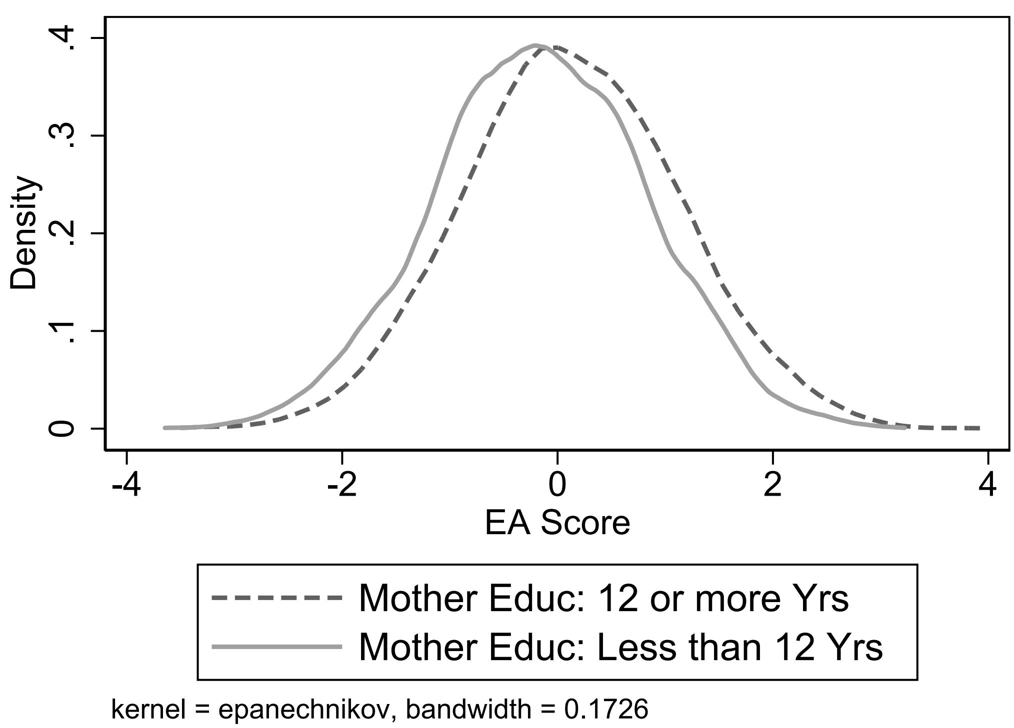


Figure 2: Distribution of the EA Score.

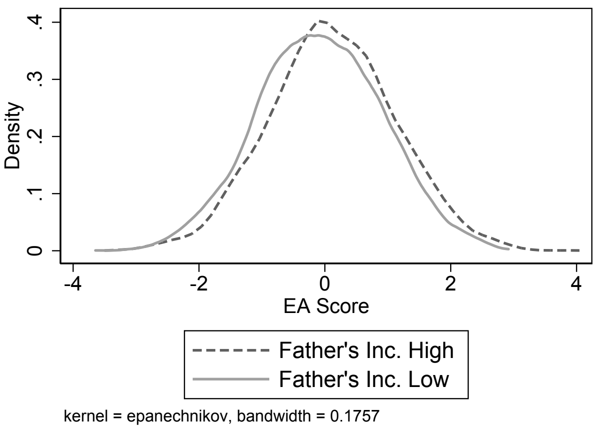


Panel (A) EA Score Distribution by College Completion

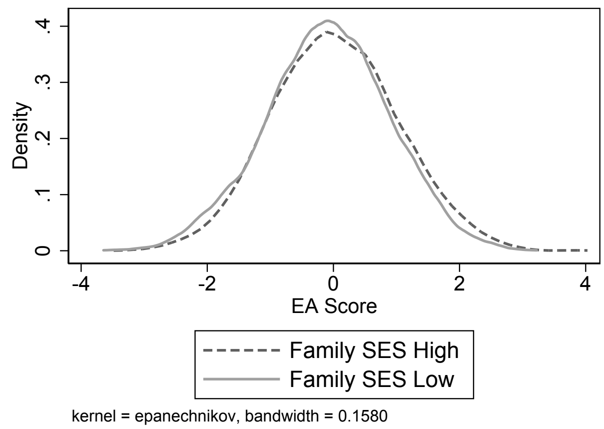


Panel (B) EA Score Distribution by Mother's Education

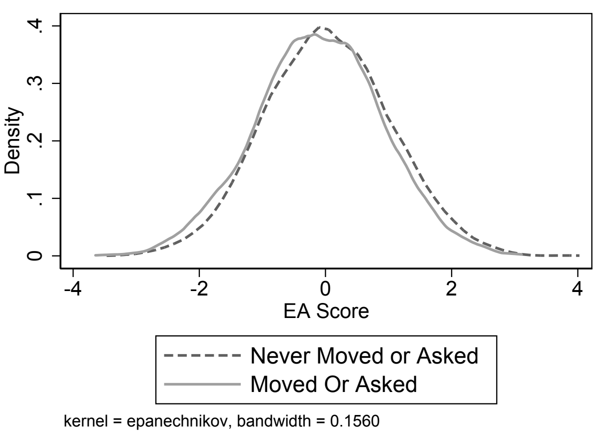
Figure 3: EA Score Distribution by Own and Maternal Education.



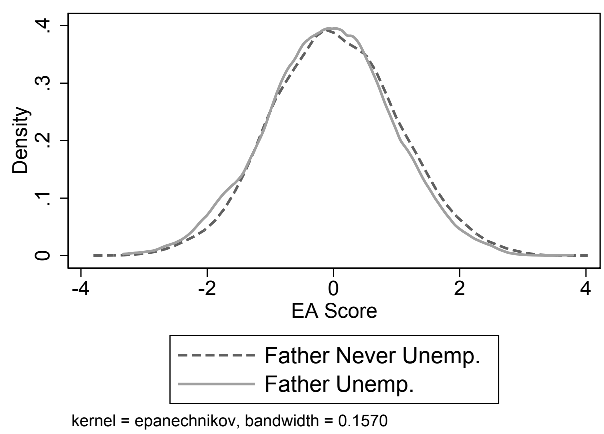
Panel (A) SES Measure: Father's Income



Panel (B) SES Measure: Family Well Off

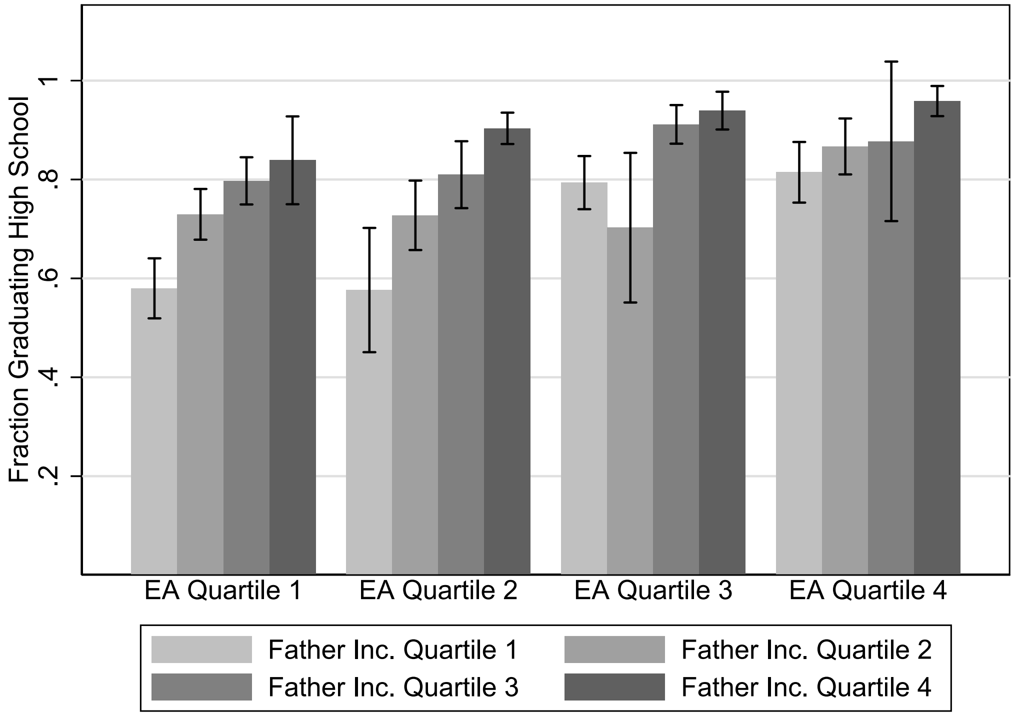


Panel (C) SES Measure: Never Moved/Asked for Help

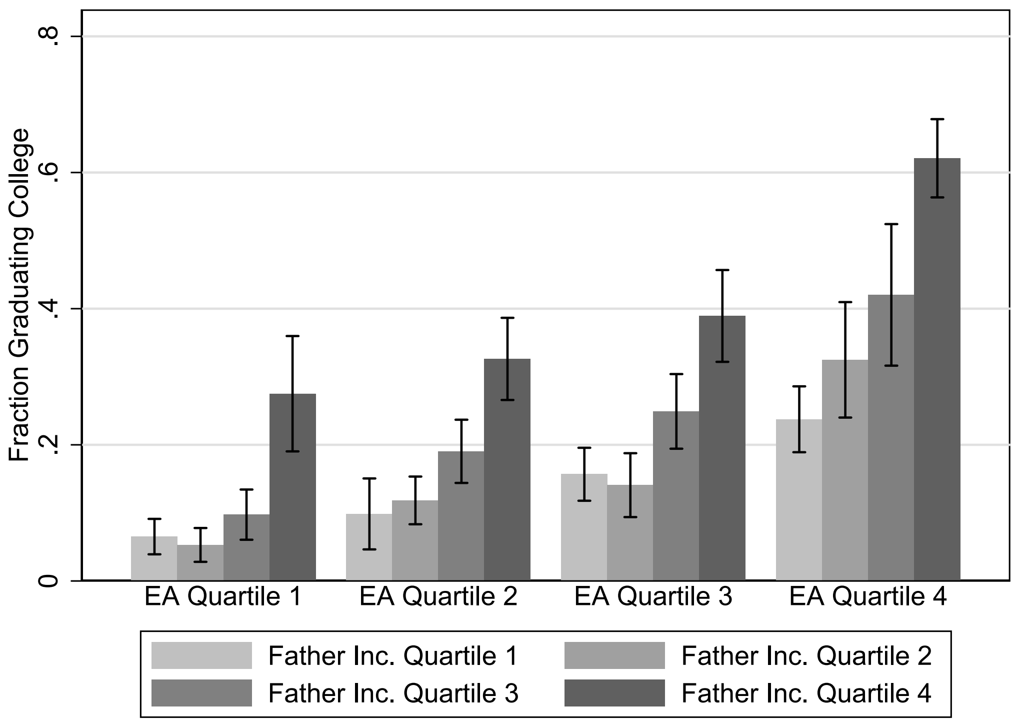


Panel (D) SES Measure: Father's Unemployment

Figure 4: EA Score Distribution by Family SES.

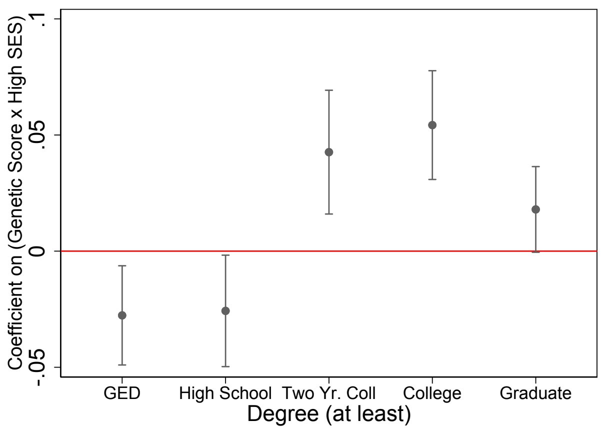


Panel (A) High School Graduation by EA Score and Father's Income

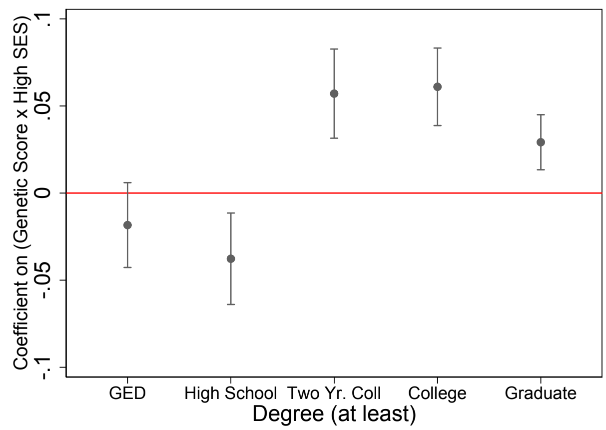


Panel (B) College Graduation by EA Score and Father's Income

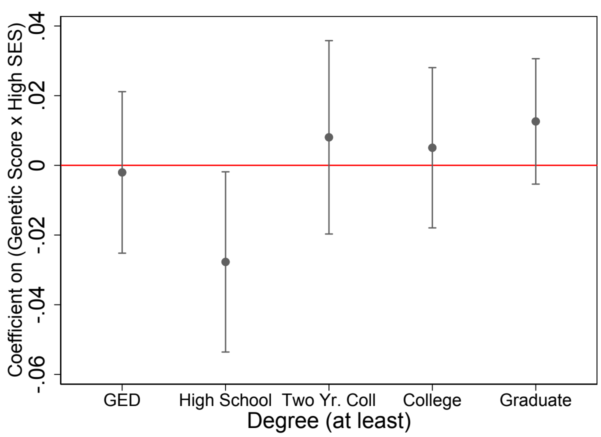
Figure 5: Educational Attainment by Father's Income and EA Score. Bars are plotted with 95 percent confidence intervals.



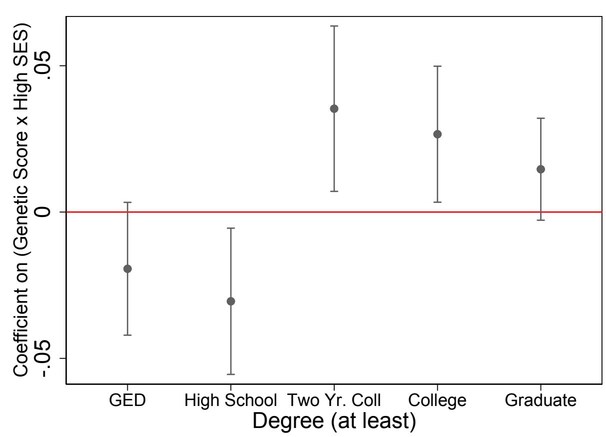
Panel (A) SES Measure: Father's Income



Panel (B) SES Measure: Family Well Off

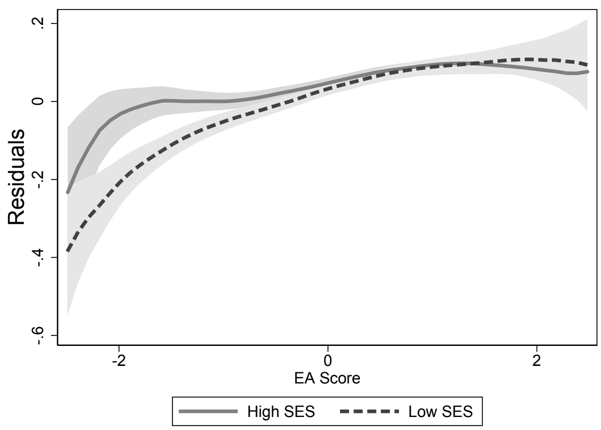


Panel (C) SES Measure: Never Moved/Asked for Help

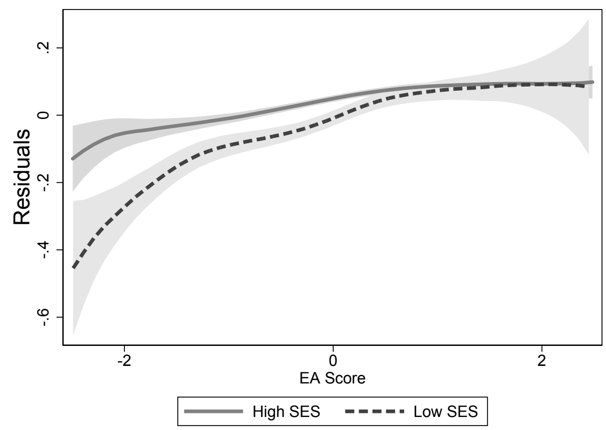


Panel (D) SES Measure: Father's Unemployment

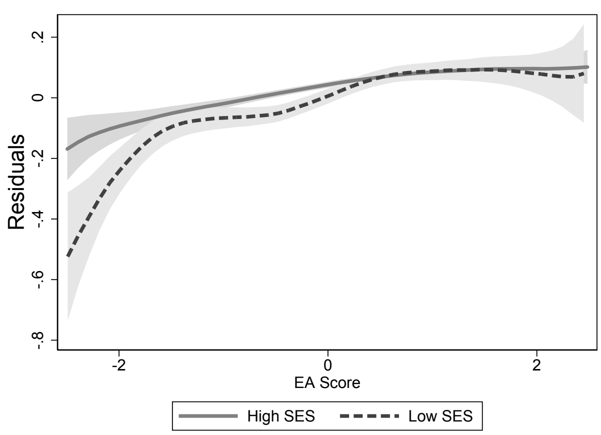
Figure 6: Coefficient on the interaction between EA score and high SES for different schooling categories with 95 percent confidence intervals.



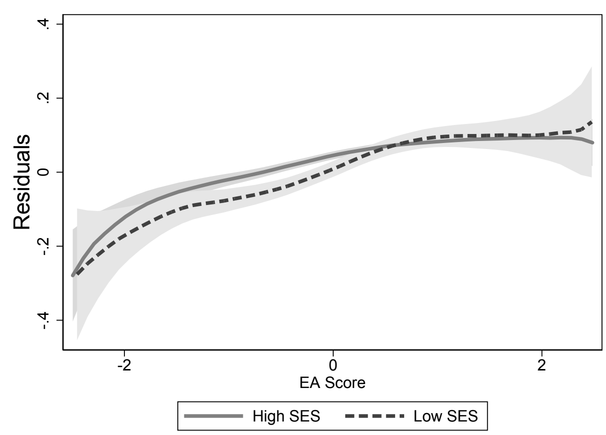
Panel (A) SES Measure: Father's Income



Panel (B) SES Measure: Family Well Off

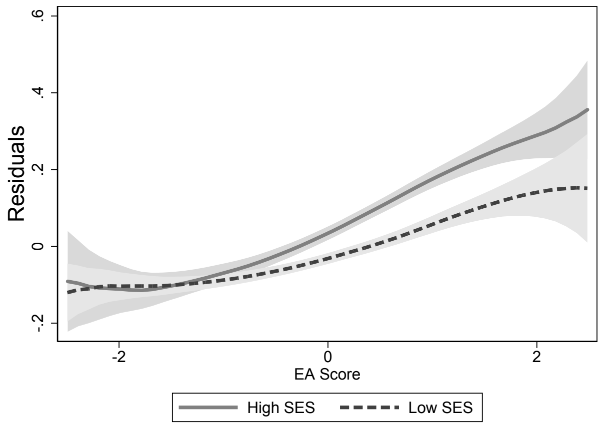


Panel (C) SES Measure: Never Moved/Asked for Help

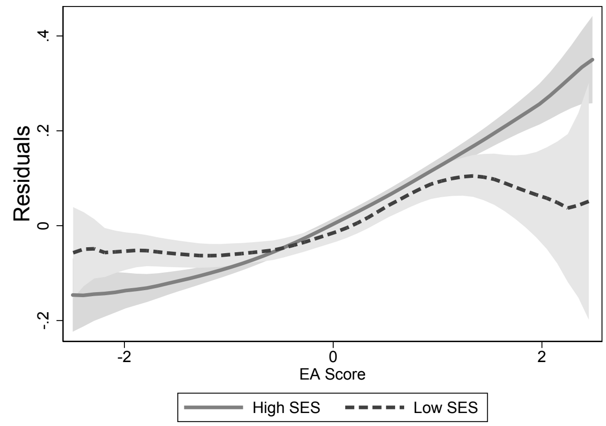


Panel (D) SES Measure: Father's Unemployment

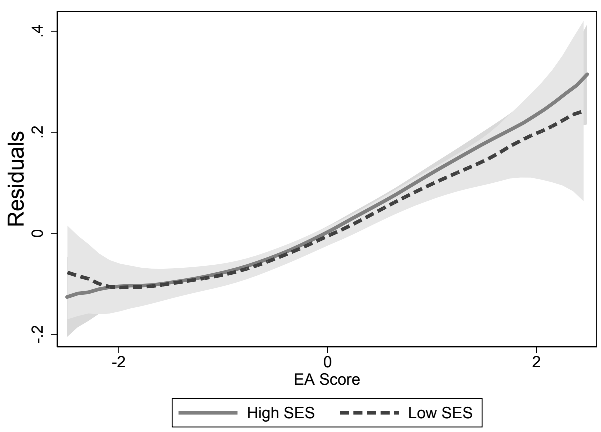
Figure 7: Non-parametric (local polynomial) estimation relating the probability of high school degree or more to EA score for high versus low SES for different measures of childhood SES. In each panel, the outcome variable is the residual from OLS regression of an indicator for completing a high school degree or more onto a set of controls and the regressor is EA score. Shaded areas depict 95 percent confidence intervals.



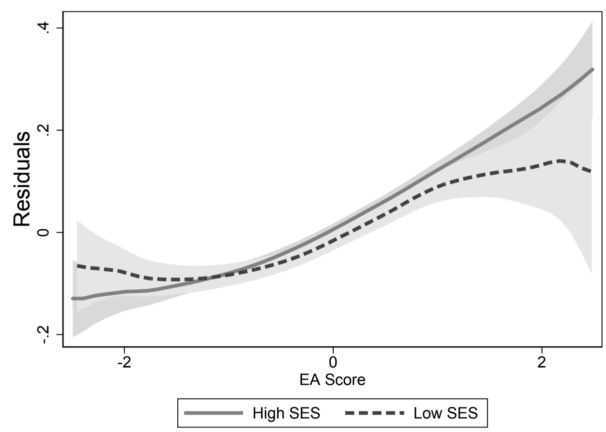
Panel (A) SES Measure: Father's Income



Panel (B) SES Measure: Family Well Off

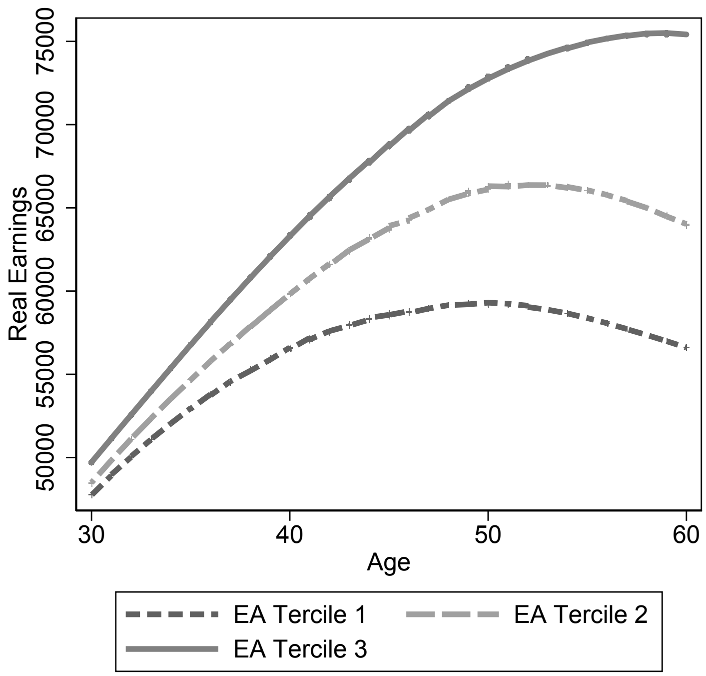


Panel (C) SES Measure: Never Moved/Asked for Help

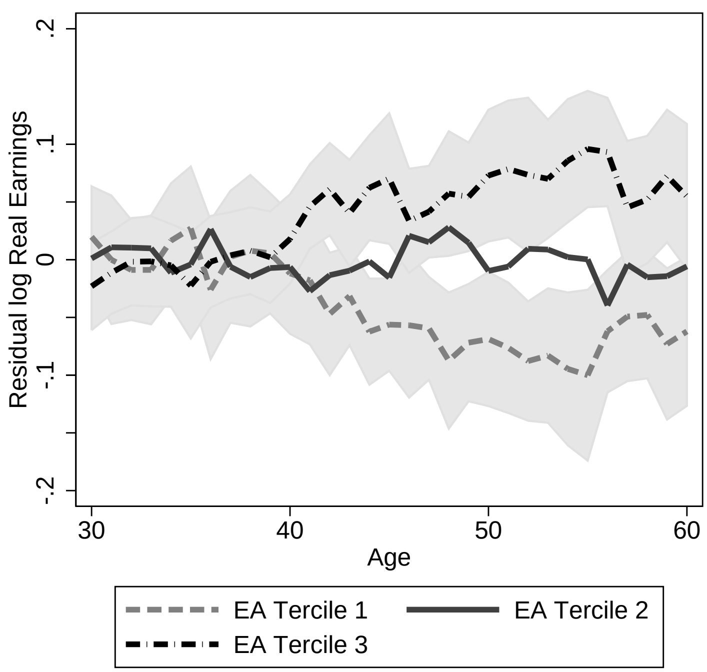


Panel (D) SES Measure: Father's Unemployment

Figure 8: Non-parametric (local polynomial) estimation relating the probability of completing a college degree or more to EA score for high versus low SES for different measures of childhood SES. In each panel, the outcome variable is the residual from OLS regression of an indicator for completing a college degree or higher onto a set of controls and the regressor is EA score. Shaded areas depict 95 percent confidence intervals.



Panel (A) Earnings Over the Life-Cycle by EA Score Terciles.



Panel (B) Residual log Earnings Over the Life-Cycle by EA Score Terciles

Figure 9: The EA Score and Life-Cycle Income. Panel A plots the non-parametric (lowess) relationship between age and earnings levels by EA tercile. Panel B plots mean residual log earnings for each age by EA score tercile. Shaded areas depict 95 percent confidence intervals around these means for the top and bottom terciles.

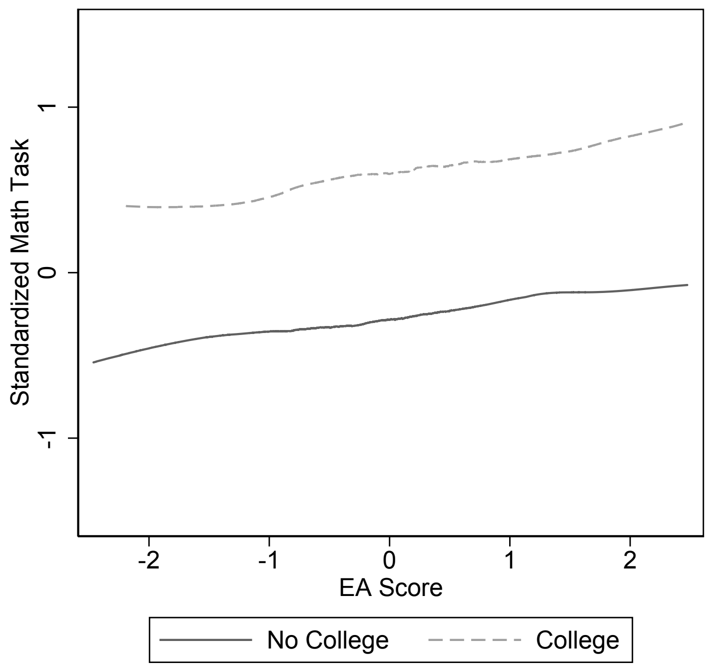


Figure 10: The EA Score and Math Task (Non-Routine Analytic). Non-parametric (lowess) estimation relating non-routine analytic task intensity to the EA score separately for those with and without a college degree.

Online Appendix:

"Genes, Education and Labor Market Outcomes:
Evidence from the Health and Retirement Study"
By: Nicholas W. Papageorge and Kevin Thom

Appendix A provides additional details on construction of the EA score. Appendix B discusses additional results and robustness checks discussed throughout the main text. Appendix C provides a model of measurement error that helps to guide our interpretation of estimates. In Appendix D, we relate the EA score to a cognitive test score available for HRS respondents. Appendix E describes how we weight observations due to possible sample selection issues along with our approach to correcting standard errors due to multiple hypothesis testing.

A Additional Details on GWAS and Construction of the EA Score

In this appendix, we provide a brief introduction to molecular genetics and the kinds of genetic data that we use in this study. We repeat some portions of Section 2 so that this appendix can provide a self-contained introduction to GWAS and the EA score used in our analysis. First, we describe some basic features of the human genome. Next, we discuss how statistical gene-discovery projects can produce scores that are useful for the prediction of economic outcomes such as educational attainment. We highlight how recent advances permit credible and replicable inference.

The human genome consists of approximately 3 billion nucleotide pairs spread out over 23 chromosomes.[68] A DNA molecule is often thought of as double-helix ladder, with the nucleotide base pairs forming the "rungs" of the ladder. Each rung can either be an adenine-thymine pair, or a guanine-cytosine pair. If the DNA strand can be thought of as a ladder with nucleotide-pair rungs, then the rails or sides of the ladder are formed by phosphate and sugar molecules. These rails can be distinguished as either the positive (+) or negative (−) strands. At a particular location, it will matter which nucleotide molecule is attached to which strand. For example, if there is an adenine-thymine pair in a particular position where the adenine molecule is attached to the positive strand, this would be denoted by an A. However, if instead the thymine molecule were attached to the positive strand, this would be denoted by a T. This means that four possible variants could exist at a given address: A, T, G or C, depending on which nucleotide pair is present, and the position of that pair relative to the positive strand. However, most SNPs are biallelic, meaning that there are only

[68]Most of the background information presented here on the human genome follows Beauchamp et al. (2011) and Benjamin et al. (2012)

two observed alleles at a particular location. The human genome can therefore be thought of as a series of 3 billion genetic addresses, each of which contains a particular base pair molecule in a particular position.

At the vast majority of such locations (about 99 percent), there is no variation in the observed nucleotide pair. A single-nucleotide polymorphism (SNP) exists when there are differences in the nucleotide pair present at a particular location on the genome. A particular SNP can be referred to by a name (e.g., rs7937), which indicates its position in the genome. An allele refers to one of the variants that may be present at a particular SNP. If T (an adenine-thymine pair with the thymine attached to the positive strand) is more commonly found at a particular SNP, it is referred to as the major allele, and the other observed allele is referred to as the minor allele.[69]

A traditional approach to the discovery of gene-behavior associations rests on examining *candidate genes*. Under this paradigm, researchers use some knowledge of the relevant biological processes to suggest places in the genome that might contain SNPs associated with a particular outcome. Unfortunately, this approach to identifying gene-economic outcomes has also generated a large number of reported associations that have failed to replicate outside of their discovery samples. This problem has been so widespread that an editorial statement from the journal *Behavior Genetics* stated that "[t]he literature on candidate gene associations is full of reports that have not stood up to rigorous replication," and that "it now seems likely that many of the published findings of the last decade are wrong or misleading and have not contributed to real advances in knowledge," (Hewitt, 2012). This pattern has emerged, in part, because traditional candidate gene studies have been severely underpowered to detect real genetic effects. Sample sizes in general have been too small relative to the true effect sizes of individual SNPs, making it likely that statistically significant associations are the result of chance. This problem is exacerbated when studies search over many candidate genes, creating a multiple hypothesis testing problem that increases the likelihood of finding false positive results (Benjamin et al., 2012).

An alternative to candidate genes is an approach called a genome-wide association study (GWAS). Under the GWAS methodology, researchers scan the entire genome for SNPs that are associated with a particular phenotype (trait or outcome), but adopt strong measures to deal with multiple hypothesis testing. For a particular outcome of interest, y_i, and for a set of observed SNPs, $\{SNP_{ij}\}_{j=1}^{N^J}$, a GWAS study proceeds by obtaining estimates of N^J separate regressions of the form:

$$y_i = \mu X_i' + \beta_j SNP_{ij} + \epsilon_{ij} \tag{2}$$

[69]In the case of SNPs that are not biallelic, there may be multiple minor alleles.

Here SNP_{ij} measures the number of copies of a reference allele possessed by individual i for SNP j. For example, if the reference allele at SNP j is AT, then SNP_{ij} could take the values 0, 1, or 2. The maximum value of 2 reflects the fact that an individual can have at most two copies of the reference allele — one on each inherited chromatid. Additionally, X_i is a vector of controls, including principal components of the genetic variables $\{SNP_{ij}\}_{j=1}^{N^J}$. Principal components of the genetic data are added to control for population stratification. For example, it could be that SNP_{ij} is correlated with a particular ethnicity or ancestry group. Failure to control for the principal components could generate observed SNP-phenotype relationships that reflect the influence of broader ethnic differences rather than the influence of a particular genetic marker.

After obtaining estimates for all N^J versions of equation (2), those estimated coefficients $\widehat{\beta}_j$ with sufficiently small p-values are said to reflect relationships that are genome-wide significant. Given the huge number of regressions run under this methodology, the significance thresholds in modern GWAS are typically very strict. A conventional threshold is 5×10^{-8}. This approach has become popular and, as a consequence of its stringency requirements, has led to the discovery of a number of credible genetic associations. For example, the well-known FTO gene for obesity was discovered through a GWAS, despite the lack of any existing biology that would have suggested it as a candidate gene (Benjamin et al., 2012).

Existing work has demonstrated the importance of credibly identified SNPs for several economic outcomes. These SNPs either directly emerged from a GWAS, or were candidate genes that were validated by later GWAS results. An established literature documents a number of credible genetic associations with smoking behaviors (Bierut, 2010; Thorgeirsson et al., 2010). Fletcher (2012) demonstrates that a SNP associated with smoking intensity also appears to moderate the effect of tobacco taxes. More closely related to our work, another set of studies suggests indirect linkages between genetic variants and human capital. For example, Fletcher and Lehrer (2011) use a set of SNPs associated with health outcomes to provide exogenous within-family variation to estimate a causal relationship between health and education. Finally, Thompson (2014) shows that a variant associated with the MAOA gene appears to moderate the relationship between income and education.

Recent work using GWAS has discovered some of the first direct associations between specific SNPs and education. Rietveld et al. (2013) identified three SNPs (rs9320913, rs11584700, rs4851266) attaining genome-wide significance in a GWAS for educational attainment. Follow-up work by the same team (the Social Science and Genetics Association Consortium) has recently extended the Rietveld et al. (2013) study to perform an educational attainment GWAS with a sample size of 293,723. This follow-up study, Okbay et al. (2016), has discovered 74 SNPs that attain genome-wide significance. In a second follow-up using a sample size of over 1.1 million, Lee et al. (2018) reports over 1,000 genome-wide significant SNPs and generates the most predictive EA score to date. We build our analysis here on the gene-education associations found in this follow-up study.

One common technique adopted in the GWAS literature is to take observed SNPs and the estimated GWAS coefficients (the $\widehat{\beta}_j$) and aggregate them into a polygenic score that can be used for prediction. Typically these scores take the following form:

$$PGS_i = \sum_j \widetilde{\beta}_j SNP_{ij} \tag{3}$$

where $\widetilde{\beta}_j$ is some transformation of the underlying GWAS coefficients. The $\widehat{\beta}_j$ estimates are typically corrected to account for correlation between SNPs and prevent over or under prediction. In our study, we use SNP weights $\widehat{\beta}_j$ that have been adjusted using the Bayesian LDpred technique developed by Vilhjálmsson et al. (2015), and applied to the genetic data in the HRS.[70] We refer to the polygenic score created using these weights as the *EA score*, to indicate that this is a score developed to predict "Educational Attainment".

[70] We would like to especially thank Aysu Okbay, a member of the Social Science and Genetics Consortium, for graciously generating and sharing some of the scores that are not otherwise publicly available. We note as well that the polygenic score that we use in this study combines all SNPs analyzed in Lee et al. (2018), not just those reaching genome-wide significance.

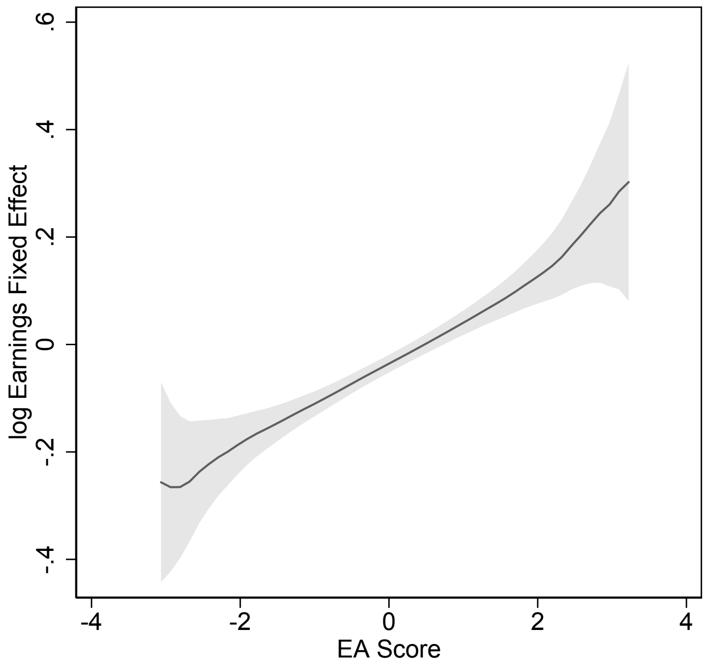
B Additional Results and Robustness Checks

This appendix contains a series of additional analyses and robustness checks. In Appendix B.1 we address the relationship between the EA score and fixed effects in an earnings regression. Appendix B.2 provides suggestive evidence on mechanisms explaining the gene-SES interactions we estimate. In Appendix B.3, we present coefficient estimates for interaction terms between the EA score and childhood SES in regressions predicting degree outcomes. In Appendix B.4, we replicate results on SES and education for men and women separately (and pooling genders, but with a male interaction term). In Appendix B.5, we show results using alternative EA scores. Appendix B.6 provides additional information and results on income. Appendix B.7 discusses the EA score and labor supply. Finally, Appendix B.8 investigates the joint distribution of father's income, the EA score, and earnings.

B.1 The EA Score and Fixed Effects

Fixed-effects models are often estimated to control for time-invariant characteristics, including genetic factors, in models of earnings and other outcomes over the life-cycle. Here we examine the relationship between the EA score and estimated fixed effects from our SSA earnings sample. We first estimate a regression of log earnings on year dummies, age dummies, and individual fixed effects for our earnings panel. We next extract estimates of the fixed effects from this regression and examine their relationship with the EA score. Figure S1 plots the non-parametric relationship between the EA score and the fixed effects. There is a strong, positive, and approximately linear relationship between the EA score and the fixed effects. The correlation between these two variables is $\rho = 0.177$, and in a bivariate regression of the fixed effects on the EA score, the incremental R^2 associated with the EA score is 0.0313. The strong relationship between the fixed effects and the EA score is unsurprising, since the fixed effects absorb the substantial relationship between education and earnings, and the EA score is highly correlated with educational attainment.

In traditional fixed effects models, including the one we estimate here, an individual fixed effect shifts the mean of the outcome variable by the same amount in every period. However, as demonstrated in Panel B of Figure 9, the relationship between the EA score and log-earnings appears to grow over the life-cycle. This pattern is obscured in the fixed effects results, and in subsequent analyses relating the EA score to the estimated fixed effects.



Appendix Figure S1: The EA Score and Log Earnings Fixed Effect. Non-parametric (local polynomial) estimation relating the EA score and the estimated fixed effect for earnings. Shaded areas depict 95 percent confidence intervals.

B.2 Specific Investments: Books in the Household, Preschool, and Household Size

The results in Section 3.4 suggest that childhood SES can moderate the relationship between the EA score and educational attainment. However, the mechanisms that give rise to this relationship remain unclear. For example, higher father's income might relax credit constraints that prevent high-score children from pursuing a college degree, increasing the relationship between the EA score and possessing a college degree. Alternately father's income might also be associated with early life investments like preschool that could differentially affect later-life outcomes depending on an individual's genetic endowments. The policy implications of these results depend on which mechanisms gives rise to the moderation found in Section 3.4.

The literature on early childhood skill formation has examined the impact of preschool (Heckman, Pinto, and Savelyev, 2013) and books in the household (Cunha, Heckman, and Schennach, 2010) on subsequent human capital formation. Moreover, the literature on the quantity-quality tradeoff in fertility suggests that households with fewer resources might choose to have more children and make lower human capital investments in these children

(Becker, 1960; Hotz, Klerman, and Willis, 1997). The two waves of the *Life History Mail Survey* from the HRS provide an opportunity to examine the role of these specific features of the environment. Specifically, the *Life History Mail Survey* contains items that ask the respondent whether they attended a preschool program before starting elementary school, how many non-school books were present in their home at age 10, and how many people were living in the household when the respondent was 10. The books question allows the following categorical responses: (i) None or very few (0-10 books); (ii) enough to fill one shelf (11-25 books); (iii) enough to fill one book case (26-100 books); (iv) enough to fill two book cases (101-200 books); and (v) enough to fill more than two bookcases (more than 200 books). We create a binary variable indicating a high number of books in the household if the respondent says there were at least enough books to fill one book case (26 or more books). For the household size question, we create a binary indicating the presence of more than five people in the house.

The first three columns of Table S1 regress educational outcomes on our standard controls (including parental education), the EA score, and the variables measuring preschool attendance, books in the household, and household size. We examine years of schooling and indicators for completing at least a high school degree and at least a (four year) college degree as outcomes. We find that a high number of books in the household predicts higher educational attainment for all of these educational outcomes, while having more people in the house is negatively associated with all educational outcomes. These associations are substantial in size. For example, having at least one book case full of books is associated with a 13 percentage point increase in the probability of earning a college degree. We find more mixed associations for the preschool variable. Preschool attendance positively predicts earning a college degree (p-value<0.01), as well as years of schooling (p-value<0.05). We also unexpectedly find a negative association between preschool status and earning at least a high school degree.

Columns (4)-(6) of Table S1 regress the high books, preschool, and household size indicators on our standard controls, the EA score, and the four family SES variables from Section 3.4. We find that all four SES variables significantly predict having a high number of books in the house. We note, however, that the association between the "father never unemployed" measure and the indicator for many books in the household is only marginally significant (p-value<0.10). High father's income exhibits a positive and significant association with preschool attendance. High father's income and the "Family Well Off" measures are both significant negative predictors of household size. Taken together, the results in Table S1 indicate that the number of books in the household is strongly associated with completed educational outcomes, and that the high family SES variables used earlier tend to predict higher propensities for making these investments. We also find fairly strong evidence linking household size to the at least two of the SES measures. The associations between preschool, education, and SES are weaker and less consistent. This provides suggestive evidence that early childhood investments like books could be among the mechanisms through which high SES operates to influence educational achievement and moderate the relationship between the EA score and education.

Appendix Table S1: Family SES Measures and Specific Human Capital Measures

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var.	Educ	At least High School	At least College	High Books	Preschool	> 5 in House
EA Score	0.570***	0.052***	0.115***	0.036***	0.026***	0.010
	(0.039)	(0.007)	(0.008)	(0.011)	(0.009)	(0.012)
High Num. of Books	0.838***	0.067***	0.130***			
	(0.096)	(0.015)	(0.017)			
Pre-School	0.312**	-0.051**	0.134***			
	(0.132)	(0.023)	(0.030)			
> 5 in House	-0.515***	-0.055***	-0.047***			
	(0.082)	(0.015)	(0.016)			
High Father's Inc.				0.059**	0.049***	-0.067**
				(0.023)	(0.018)	(0.027)
Family Well Off				0.095***	0.033*	-0.135***
				(0.031)	(0.020)	(0.032)
Never Move or Ask Help				0.093***	0.008	0.017
				(0.029)	(0.023)	(0.031)
Father Not Unemp.				0.048*	0.018	0.037
				(0.029)	(0.022)	(0.033)
Obs.	3981	3966	3966	3184	3163	3212
R^2	0.336	0.192	0.284	0.292	0.176	0.113

All regressions include the first 10 principle components of the full matrix of genetic data as controls, a full set of birth year dummies, a male dummy, interactions between the birth year and male dummies, and controls for parental education.

B.3 Regression Estimates for Interactions between SES and the EA Score

Here we present the coefficient estimates for the specifications that regress dummy variables for completed degree levels on the EA score, family SES measures, and interactions between the EA score and family SES. Each panel of Table S2 presents estimates of Equation 1 for a different binary SES measure. The estimates for the interaction terms, along with the associated 95 percent confidence intervals, are plotted in Figure 6 of the main text.

Appendix Table S2: Polygenic Score and Interactions with SES

Dep Var: At Least	(1) H.S. Equiv	(2) High School	(3) Two Yr.	(4) College	(5) Grad
Panel A: SES Measure - Father Occ. Income					
EA Score	0.056***	0.066***	0.079***	0.083***	0.037***
	(0.011)	(0.012)	(0.013)	(0.012)	(0.009)
High SES	0.062***	0.063***	0.103***	0.090***	0.021**
	(0.013)	(0.015)	(0.014)	(0.012)	(0.009)
EA Score × High SES	-0.028**	-0.026**	0.043***	0.054***	0.018*
	(0.011)	(0.012)	(0.014)	(0.012)	(0.009)
Obs.	6750	6750	6750	6750	6750
R^2	0.283	0.269	0.255	0.262	0.136
Panel B: SES Measure - Family Well Off					
EA Score	0.062***	0.087***	0.055***	0.064***	0.024***
	(0.013)	(0.014)	(0.014)	(0.012)	(0.009)
High SES	0.052***	0.080***	0.039***	0.031***	0.005
	(0.013)	(0.015)	(0.014)	(0.012)	(0.008)
EA Score × High SES	-0.018	-0.038***	0.057***	0.061***	0.029***
	(0.012)	(0.013)	(0.013)	(0.011)	(0.008)
Obs.	8387	8387	8387	8387	8387
R^2	0.259	0.253	0.228	0.241	0.132
Panel C: SES Measure - Move or Asked for Help					
EA Score	0.048***	0.077***	0.093***	0.107***	0.038***
	(0.012)	(0.014)	(0.016)	(0.013)	(0.010)
High SES	0.028**	0.048***	0.022	0.025**	0.002
	(0.014)	(0.016)	(0.015)	(0.012)	(0.008)
EA Score × High SES	-0.002	-0.028**	0.008	0.005	0.013
	(0.012)	(0.013)	(0.014)	(0.012)	(0.009)
Obs.	8362	8362	8362	8362	8362
R^2	0.258	0.248	0.224	0.238	0.130
Panel D: SES Measure - Father Unemployed					
EA Score	0.061***	0.080***	0.071***	0.090***	0.036***
	(0.012)	(0.013)	(0.016)	(0.013)	(0.010)
High SES	0.012	0.028*	0.029**	0.029**	0.009
	(0.014)	(0.015)	(0.014)	(0.012)	(0.008)
EA Score × High SES	-0.019*	-0.030**	0.035**	0.027**	0.015*
	(0.012)	(0.013)	(0.014)	(0.012)	(0.009)
Obs.	8402	8402	8402	8402	8402
R^2	0.255	0.246	0.223	0.237	0.129

Regressions relating educational attainment categories to the EA score and childhood SES along with interactions between the EA score and high SES. Regressions also include a full set of dummy variables for birth year, a male dummy and a full set of interactions between the birth year and gender dummies. Additionally, every specification includes the first 10 principle components of the full matrix of genetic data, a cubic in the EA score, and controls for parental education (years of paternal and maternal education and dummies indicating missing values for each).

B.4 Additional Results on Gender Differences

Analyses in Section 3 on education and childhood SES examine males and females together while our analyses in Section 4 limit attention to males. In choosing these analytic samples, the aim is to keep the largest sample possible unless there is a compelling reason to do otherwise. Given selection into the labor market among females, especially those in the older HRS cohorts, there is good reason to focus on males when studying earnings. In this section, we assess whether results from Section 3 on education and SES change if we consider males and females separately. Tables S3-S4 replicate the specifications for years of education in Table 2 separately for men and women, respectively. Table S5 again estimates these specifications using the pooled sample of men and women, but now adds an interaction term between the EA score and a dummy for male respondents. The results in these tables suggest that the EA score strongly predicts years of schooling for both men and women conditional on a rich set of controls. The interaction results in Table S5 provide evidence that the association between the EA score and years of schooling is larger for men. This gender difference merits exploration in future research. Tables S6 and S7 replicate the degree specifications in Table 3 for males and females, respectively. We find that the EA score tends to predict college completion more strongly for men than for women.

Finally, we present estimates of the specifications with interactions between SES and the EA score separately by gender. Tables S8-S9 provide estimates of the interaction specifications in Equation 1 for men and women, respectively. The results for these specifications with our main pooled sample are found in Figure 6 and Table S2. The results in Tables S8-S9 are largely consistent with our baseline results from the pooled sample. We find evidence of interactions between SES and the EA score in both males and females, although the coefficients are less precisely estimated. This could arise because of the smaller sample sizes generated by splitting the sample.

Appendix Table S3: Polygenic Score and Educational Attainment for Males

	(1)	(2)	(3)	(4)	(5)
EA Score	0.889***	0.651***	0.642***	0.616***	0.666***
	(0.073)	(0.071)	(0.070)	(0.066)	(0.048)
Father Educ		0.162***	0.160***	0.099***	0.118***
		(0.023)	(0.023)	(0.025)	(0.021)
Mother Educ		0.135***	0.132***	0.098***	0.118***
		(0.028)	(0.028)	(0.026)	(0.025)
Child Health: Very Good			-0.308	-0.295	-0.307***
			(0.237)	(0.206)	(0.113)
Child Health: Good			-0.435**	-0.390**	-0.738***
			(0.216)	(0.198)	(0.145)
Child Health: Fair			-0.006	-0.061	-0.543**
			(0.321)	(0.293)	(0.250)
Child Health: Poor			0.202	0.361	-0.221
			(0.689)	(0.650)	(0.611)
Child Health: Missing			2.351***	2.494	4.366**
			(0.655)	(1.687)	(2.047)
Obs.	3560	3560	3560	3560	3560
R^2	0.272	0.394	0.397	0.436	0.599
Child SES Measures	N	N	N	Y	Y
Child Region	N	N	N	N	Y
Religion	N	N	N	N	Y

Regressions relating educational attainment (years) to the EA score for males. All regressions include a full set of dummy variables for birth year. All specifications include the first 10 principle components of the full matrix of genetic data as controls. Some specifications include controls for parental education, childhood health, childhood SES measures, region during childhood and religion, as indicated.

Appendix Table S4: Polygenic Score and Educational Attainment for Females

	(1)	(2)	(3)	(4)	(5)
EA Score	0.809***	0.586***	0.588***	0.574***	0.530***
	(0.058)	(0.049)	(0.050)	(0.056)	(0.040)
Father Educ		0.135***	0.132***	0.113***	0.098***
		(0.015)	(0.014)	(0.019)	(0.016)
Mother Educ		0.201***	0.198***	0.190***	0.181***
		(0.017)	(0.017)	(0.018)	(0.017)
Child Health: Very Good			-0.009	0.033	0.005
			(0.103)	(0.094)	(0.088)
Child Health: Good			-0.158	-0.115	-0.159
			(0.126)	(0.116)	(0.105)
Child Health: Fair			-0.283	-0.259	-0.318*
			(0.177)	(0.176)	(0.176)
Child Health: Poor			-1.190	-1.102	-1.191
			(0.801)	(0.742)	(0.754)
Child Health: Missing			-	-	-
			-	-	-
Obs.	4977	4977	4977	4977	4977
R^2	0.231	0.342	0.346	0.355	0.417
Child SES Measures	N	N	N	Y	Y
Child Region	N	N	N	N	Y
Religion	N	N	N	N	Y

Regressions relating educational attainment (years) to the EA score for females. All regressions include a full set of dummy variables for birth year. All specifications include the first 10 principle components of the full matrix of genetic data as controls. Some specifications include controls for parental education, childhood health, childhood SES measures, region during childhood and religion, as indicated.

Appendix Table S5: Polygenic Score and Educational Attainment - EA Score x Male

	(1)	(2)	(3)	(4)	(5)
EA Score	0.809***	0.566***	0.562***	0.540***	0.505***
	(0.058)	(0.051)	(0.051)	(0.056)	(0.041)
EA Score x Male	0.080	0.107	0.108	0.110	0.186***
	(0.093)	(0.083)	(0.083)	(0.084)	(0.061)
Father Educ		0.147***	0.144***	0.107***	0.110***
		(0.013)	(0.013)	(0.016)	(0.013)
Mother Educ		0.173***	0.170***	0.149***	0.150***
		(0.016)	(0.016)	(0.016)	(0.015)
Child Health: Very Good			-0.144	-0.103	-0.126*
			(0.123)	(0.114)	(0.070)
Child Health: Good			-0.266**	-0.198*	-0.423***
			(0.123)	(0.120)	(0.089)
Child Health: Fair			-0.204	-0.120	-0.392***
			(0.165)	(0.171)	(0.145)
Child Health: Poor			-0.658	-0.554	-0.860
			(0.575)	(0.570)	(0.570)
Child Health: Missing			1.526***	1.066	1.982
			(0.408)	(1.173)	(1.269)
Obs.	8537	8537	8537	8537	8537
R^2	0.256	0.363	0.364	0.382	0.516
Child SES Measures	N	N	N	Y	Y
Child Region	N	N	N	N	Y
Religion	N	N	N	N	Y

Regressions relating educational attainment (years) to the EA score for males and females including a dummy variable for male interacted with the EA score. All regressions include a full set of dummy variables for birth year. All specifications include the first 10 principle components of the full matrix of genetic data as controls. Some specifications include controls for parental education, childhood health, childhood SES measures, region during childhood and religion, as indicated.

Appendix Table S6: Polygenic Score and Categorical Education Outcomes for Males

Dep Var.	(1) No Degree	(2) Two-Year Coll.	(3) College	(4) College Plus	(5) Redo Grade
Panel A:					
EA Score	-0.066***	-0.003	0.065***	0.081***	-0.052***
	(0.008)	(0.005)	(0.008)	(0.007)	(0.008)
Obs.	3551	3551	3551	3551	3398
R^2	0.192	0.060	0.067	0.105	0.073
Panel B:					
EA Score	-0.046***	-0.004	0.049***	0.067***	-0.042***
	(0.007)	(0.005)	(0.007)	(0.006)	(0.009)
Father Educ	-0.012***	0.001	0.012***	0.014***	-0.012***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)
Mother Educ	-0.009***	0.002	0.013***	0.008***	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Obs.	3551	3551	3551	3551	3398
R^2	0.271	0.066	0.105	0.138	0.084

Regressions relating educational attainment categories or the probability of repeating a grade to the EA score for males. Specifications in Panel A do not include parental education. Specifications in Panel B include parental education. All regressions include a full set of dummy variables for birth year. Additionally, every specification includes the first 10 principle components of the full matrix of genetic data.

Appendix Table S7: Polygenic Score and Categorical Education Outcomes for Females

	(1)	(2)	(3)	(4)	(5)
Dep Var.	No Degree	Two-Year Coll.	College	College Plus	Redo Grade
Panel A:					
EA Score	-0.070***	-0.012**	0.071***	0.048***	-0.032***
	(0.007)	(0.006)	(0.007)	(0.005)	(0.005)
Obs.	4961	4961	4961	4961	4768
R^2	0.213	0.042	0.095	0.067	0.043
Panel B:					
EA Score	-0.053***	-0.016***	0.053***	0.037***	-0.021***
	(0.007)	(0.006)	(0.007)	(0.005)	(0.005)
Father Educ	-0.005**	-0.001	0.014***	0.009***	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Mother Educ	-0.021***	0.006***	0.014***	0.008***	-0.012***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Obs.	4961	4961	4961	4961	4768
R^2	0.250	0.048	0.135	0.092	0.064

Regressions relating educational attainment categories or the probability of repeating a grade to the EA score for females. Specifications in Panel A do not include parental education. Specifications in Panel B include parental education. All regressions include a full set of dummy variables for birth year. Additionally, every specification includes the first 10 principle components of the full matrix of genetic data.

Appendix Table S8: Polygenic Score and Interactions with SES for Males

Dep Var: At Least	(1) H.S. Equiv	(2) High School	(3) Two Yr.	(4) College	(5) Grad
Panel A: SES Measure - Father Occ. Income					
EA Score	0.035**	0.041**	0.112***	0.096***	0.040***
	(0.017)	(0.018)	(0.019)	(0.017)	(0.014)
High SES	0.085***	0.086***	0.129***	0.113***	0.044***
	(0.018)	(0.022)	(0.020)	(0.019)	(0.015)
EA Score × High SES	-0.015	0.001	0.017	0.039**	0.023
	(0.016)	(0.018)	(0.020)	(0.019)	(0.015)
Obs.	2828	2828	2828	2828	2828
R^2	0.332	0.312	0.269	0.262	0.167
Panel B: SES Measure - Family Well Off					
EA Score	0.058***	0.074***	0.073***	0.078***	0.019
	(0.019)	(0.021)	(0.019)	(0.018)	(0.013)
High SES	0.070***	0.106***	0.042**	0.037*	0.018
	(0.020)	(0.022)	(0.020)	(0.019)	(0.013)
EA Score × High SES	-0.026	-0.032*	0.067***	0.062***	0.049***
	(0.019)	(0.019)	(0.019)	(0.018)	(0.012)
Obs.	3503	3503	3503	3503	3503
R^2	0.289	0.280	0.241	0.241	0.156
Panel C: SES Measure - Move or Asked for Help					
EA Score	0.043**	0.067***	0.121***	0.124***	0.041***
	(0.018)	(0.022)	(0.021)	(0.019)	(0.015)
High SES	0.051**	0.082***	0.015	0.019	-0.003
	(0.021)	(0.023)	(0.021)	(0.019)	(0.014)
EA Score × High SES	-0.007	-0.031	0.004	0.003	0.022
	(0.017)	(0.019)	(0.019)	(0.017)	(0.013)
Obs.	3475	3475	3475	3475	3475
R^2	0.290	0.277	0.235	0.235	0.149
Panel D: SES Measure - Father Unemployed					
EA Score	0.058***	0.070***	0.105***	0.115***	0.052***
	(0.018)	(0.020)	(0.021)	(0.020)	(0.016)
HighSES	-0.010	0.013	0.026	0.020	0.010
	(0.020)	(0.022)	(0.020)	(0.020)	(0.015)
EA3ScorexHighSES	-0.033*	-0.035*	0.020	0.013	0.004
	(0.018)	(0.018)	(0.019)	(0.018)	(0.015)
Obs.	3505	3505	3505	3505	3505
R^2	0.279	0.261	0.235	0.233	0.145

Regressions relating male educational attainment categories to the EA score and childhood SES along with interactions between the EA score and high SES. Regressions also include a full set of dummy variables for birth year. Additionally, every specification includes the first 10 principle components of the full matrix of genetic data and controls for parental education (years of paternal and maternal education and dummies indicating missing values for each).

Appendix Table S9: Polygenic Score and Interactions with SES for Females

Dep Var: At Least	(1) H.S. Equiv	(2) High School	(3) Two Yr.	(4) College	(5) Grad
Panel A: SES Measure - Father Occ. Income					
EA Score	0.074***	0.086***	0.052***	0.069***	0.027***
	(0.013)	(0.015)	(0.016)	(0.014)	(0.009)
High SES	0.043**	0.043**	0.087***	0.076***	0.008
	(0.018)	(0.020)	(0.019)	(0.015)	(0.010)
EA Score × High SES	-0.036**	-0.045***	0.070***	0.075***	0.022**
	(0.014)	(0.016)	(0.018)	(0.015)	(0.011)
Obs.	3922	3922	3922	3922	3922
R^2	0.261	0.247	0.256	0.267	0.098
Panel B: SES Measure - Family Well Off					
EA Score	0.063***	0.097***	0.040**	0.053***	0.027**
	(0.016)	(0.018)	(0.018)	(0.016)	(0.011)
High SES	0.038**	0.059***	0.036**	0.023	-0.009
	(0.016)	(0.019)	(0.017)	(0.014)	(0.009)
EA Score × High SES	-0.012	-0.044**	0.051***	0.061***	0.012
	(0.016)	(0.017)	(0.017)	(0.014)	(0.011)
Obs.	4884	4884	4884	4884	4884
R^2	0.257	0.249	0.220	0.236	0.101
Panel C: SES Measure - Move or Asked for Help					
EA Score	0.055***	0.086***	0.073***	0.095***	0.033**
	(0.015)	(0.018)	(0.022)	(0.017)	(0.013)
High SES	0.012	0.022	0.026	0.026*	0.002
	(0.017)	(0.019)	(0.019)	(0.015)	(0.010)
EA Score × High SES	-0.002	-0.028	0.012	0.007	0.006
	(0.015)	(0.017)	(0.020)	(0.016)	(0.013)
Obs.	4887	4887	4887	4887	4887
R^2	0.253	0.240	0.215	0.234	0.101
Panel D: SES Measure - Father Unemployed					
EA Score	0.059***	0.084***	0.044**	0.071***	0.019*
	(0.015)	(0.017)	(0.022)	(0.017)	(0.010)
HighSES	0.031*	0.044**	0.030	0.035**	0.008
	(0.018)	(0.019)	(0.019)	(0.014)	(0.009)
EA3ScorexHighSES	-0.003	-0.022	0.048**	0.039**	0.024**
	(0.015)	(0.017)	(0.020)	(0.015)	(0.010)
Obs.	4897	4897	4897	4897	4897
R^2	0.257	0.249	0.218	0.235	0.101

Regressions relating female educational attainment categories to the EA score and childhood SES along with interactions between the EA score and high SES. Regressions also include a full set of dummy variables for birth year. Additionally, every specification includes the first 10 principle components of the full matrix of genetic data and controls for parental education (years of paternal and maternal education and dummies indicating missing values for each).

B.5 Results Using Alternative Versions of the EA Score

In this section, we examine the robustness of our main results to the use of alternate polygenic scores for educational attainment. Specifically, we replicate eight key results: (i) the relationship between years of school and the EA score controlling for parental education (Column (2) in Table 2); (ii-v) the interactions between the EA score and the High Father's Income and Family Well Off binaries in predicting having at least a high school degree and at least a college degree (Columns (2) and (4) in Panels A and B of Table S2; (vi) the relationship between log earnings and the EA score controlling for education (Column (2) in Panel A of Table 5); (vii) the interaction between the EA score and having at least a college degree in predicting earnings (Column (3) in Panel A of Table 5); and (viii) the interaction between the EA score and an indicator for years after 1980 in predicting log earnings (Column (2) in Panel b of Table 5).

The various panels of Table S10 present these results for seven different scores. The scores differ in terms of the sample size of the underlying GWAS discovery sample used to estimate the coefficients applied to the SNPs in each score. The scores also differ in terms of the method used to construct the score. For ease of comparison, Panel A presents the baseline results from this paper, which use the score based on the GWAS results from Lee et al. (2018) ($N > 1.1$ million). This score is constructed using the LDpred method described in Vilhjálmsson et al. (2015), which is a Bayesian method that adjusts the coefficient estimates assuming a reasonable distribution of effect sizes (given the known heritability of education), and corrects for correlations between SNPs that are close to one another in the genome. Panel B presents results using a score based on the Lee et al. (2018) GWAS that does not use LDpred, but instead sums up all SNPs weighted by their unadjusted GWAS coefficients. This is the score that is available in the most recent public release of polygenic scores by the Health and Retirement Study. Even though this all SNPs score is available for more individuals, in Panel B we restrict the sample so that it is directly comparable to the results using the LDpred score that we use in our main results. Panel C uses the same score as in Panel B, but now includes individuals from all four waves of genotyping (2006, 2008, 2010, and 2012). Comparing results from Panels A-C demonstrates the effect of the LDpred method, and the effect of changing sample size and composition as more waves of genotyped individuals are included. To ensure comparability, all specifications in Table S10 use the principal components distributed in the most recent version of the HRS Polygenic Score Data (PGS) file (V 3.0). These differ slightly from the principal components used in all other analyses in the paper, which are those released with the SSGAC's distribution of the LDpred polygenic score based on the Lee et al. (2018) GWAS, but only constructed for individuals genotyped in 2006 and 2008. As described in Appendix E, we construct sampling weights based on the inverse probability of participation in the collection of genetic data in 2006 and 2008. Note that when larger samples are used (e.g. in Panel C), we modify these weights so they are based on the inverse probability of being included in any of the waves of genotypic data, not just 2008 and 2006.

Panels D and E present results using an all SNPs score built on GWAS results from Okbay et al. (2016) with a smaller discovery sample size of $N = 293,723$. This is the score that has been made publicly available by the HRS for individuals who were genotyped in the 2006, 2008, 2010, and 2012 waves. This earlier-generation score is less predictive of educational attainment, but is available for more genotyped individuals than the LDpred version of the Lee et al. (2018) score, which only publicly available for individuals genotyped in 2006 and 2008. Panel D presents results using the all-SNPs Okbay et al. (2016) score restricted to the main analysis sample used in this paper. Panel E presents results using this score for all available individuals, increasing the sample size. Panel F presents results using an LDpred score based on the GWAS results from Rietveld et al. (2013) with a discovery sample of size $N = 126,559$. Panel G presents results using an all-SNPs score and unadjusted GWAS coefficients from Rietveld et al. (2013).

Comparing results across the panels of Table S10, several patterns emerge. First, as expected, the predictive power of the polygenic score grows as the sample size of the underlying GWAS discovery sample grows. This is most apparent looking at the basic association with years of school (conditional on parental education) in Column (1). The interactions between the EA score and family SES in predicting a college degree (Columns 4-5) are robustly found with all scores. The interactions in predicting having at least a high school degree (Columns 2-3) are less robust, and are only consistently found to be statistically significant when using scores based on the largest GWAS (Panels A-C). We robustly find an association between the EA score and log earnings, except for the first generation scores from Rietveld et al. (2013). We fail to estimate a significant interaction between the EA score and having a college degree in any of the specifications predicting earnings. We find significant interactions between the EA score and a post-1980 indicator for all scores. A comparison of Panels B and C, as well as Panels D and E suggests that the changing composition of the genetic sample does little to alter our main results.

Appendix Table S10: Results Using Alternate Polygenic Scores

Dep Var:	(1) Years of Educ.	(2) At Least H.S.	(3) At Least H.S.	(4) At Least Coll.	(5) At Least Coll.	(6) log Earn.	(7) log Earn.	(8) log Earn.
Panel A: LD Pred Score from Lee et al. (2018), $N > 1.1$ million								
EA Score	0.620***	0.064***	0.088***	0.083***	0.065***	0.030***	0.026***	0.009
	(0.042)	(0.012)	(0.014)	(0.012)	(0.012)	(0.009)	(0.010)	(0.007)
High Father's Inc.		0.061***		0.083***				
		(0.018)		(0.014)				
Score × High Fath. Inc.		-0.023*		0.051***				
		(0.012)		(0.012)				
Family Well Off			0.073***		0.030**			
			(0.017)		(0.015)			
Score × Fam. Well Off			-0.038***		0.060***			
			(0.013)		(0.011)			
Score × At Least Coll.							0.016	
							(0.020)	
Score × Post 1980								0.036***
								(0.013)
Obs.	8537	6750	8387	6750	8387	96721	96510	96510
R^2	0.360	0.266	0.255	0.262	0.240	0.190	0.195	0.205
Panel B: All SNPs Score from Lee et al. (2018), $N > 1.1$ million								
EA Score	0.475***	0.042***	0.044***	0.059***	0.052***	0.023**	0.021**	0.002
	(0.045)	(0.012)	(0.015)	(0.011)	(0.012)	(0.009)	(0.010)	(0.007)
High Father's Inc.		0.062***		0.086***				
		(0.018)		(0.014)				
Score × High Fath. Inc.		-0.023*		0.044***				
		(0.012)		(0.013)				
Family Well Off			0.071***		0.027*			
			(0.018)		(0.015)			
Score × Fam. Well Off			-0.013		0.041***			
			(0.014)		(0.012)			
Score × At Least Coll.							0.010	
							(0.022)	
Score × Post 1980								0.036***
								(0.013)
Obs.	8537	6750	8387	6750	8387	96721	96510	96510
R^2	0.343	0.256	0.245	0.240	0.216	0.189	0.194	0.204
Panel C: All SNPs Score from Lee et al. (2018), $N > 1.1$ million **Sample: 2006, 2008, 2010, and 2012 Waves of HRS Genetics Sample**								
EA Score	0.467***	0.057***	0.068***	0.056***	0.054***	0.025***	0.022**	0.004
	(0.033)	(0.010)	(0.012)	(0.010)	(0.010)	(0.008)	(0.009)	(0.006)
High Father's Inc.		0.068***		0.086***				
		(0.011)		(0.011)				
Score × High Fath. Inc.		-0.021**		0.056***				
		(0.009)		(0.011)				
Family Well Off			0.095***		0.030***			
			(0.012)		(0.010)			
Score × Fam. Well Off			-0.035***		0.043***			
			(0.011)		(0.010)			
Score × At Least Coll.							0.009	
							(0.017)	
Score × Post 1980								0.035***
								(0.011)
Obs.	11930	9252	11720	9252	11720	125346	125124	125124
R^2	0.322	0.235	0.232	0.226	0.208	0.190	0.193	0.205

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Regressions relating different versions of the EA score to various educational and labor outcomes examined in the main text. Regressions also include a full set of dummy variables for birth year, a male dummy and a full set of interactions between the birth year and gender dummies. Additionally, every specification includes the first 10 principle components of the full matrix of genetic data and controls for parental education (years of paternal and maternal education and dummies indicating missing values for each). Some regressions include measures of childhood SES and controls for own education, as indicated.

Appendix Table S10: Results Using Alternate Polygenic Scores (Continued from Previous Page)

Dep Var:	(1) Years of Educ.	(2) At Least H.S.	(3) At Least H.S.	(4) At Least Coll.	(5) At Least Coll.	(6) log Earn.	(7) log Earn.	(8) log Earn.
Panel D: All SNPs Score from Okbay et al. (2018), N = 293,723								
Sample: 2006 and 2008 Waves of HRS Genetics Sample								
EA Score	0.346***	0.026**	0.027*	0.038***	0.033***	0.028***	0.023**	0.004
	(0.050)	(0.013)	(0.016)	(0.011)	(0.012)	(0.009)	(0.010)	(0.007)
High Father's Inc.		0.063***		0.085***				
		(0.018)		(0.014)				
Score × High Fath. Inc.		-0.009		0.052***				
		(0.013)		(0.013)				
Family Well Off			0.072***		0.028*			
			(0.018)		(0.015)			
Score × Fam. Well Off			0.002		0.050***			
			(0.015)		(0.012)			
Score × At Least Coll.							0.025	
							(0.021)	
Score × Post 1980								0.042***
								(0.013)
Obs.	8537	6750	8387	6750	8387	96721	96510	96510
R^2	0.333	0.249	0.238	0.233	0.208	0.190	0.195	0.205
Panel E: All SNPs Score from Okbay et al. (2018), N = 293,723								
Sample: 2006, 2008, 2010, and 2012 Waves of HRS Genetics Sample								
EA Score	0.375***	0.055***	0.054***	0.049***	0.043***	0.022***	0.016*	0.001
	(0.040)	(0.009)	(0.012)	(0.010)	(0.010)	(0.008)	(0.009)	(0.006)
High Father's Inc.		0.068***		0.085***				
		(0.011)		(0.011)				
Score × High Fath. Inc.		-0.018*		0.055***				
		(0.010)		(0.011)				
Family Well Off			0.097***		0.029***			
			(0.012)		(0.010)			
Score × Fam. Well Off			-0.017		0.043***			
			(0.012)		(0.010)			
Score × At Least Coll.							0.022	
							(0.017)	
Score × Post 1980								0.034***
								(0.011)
Obs.	11930	9252	11720	9252	11720	125346	125124	125124
R^2	0.313	0.231	0.226	0.220	0.200	0.189	0.193	0.205
Continued on Next Page								

Regressions relating different versions of the EA score to various educational and labor outcomes examined in the main text. Regressions also include a full set of dummy variables for birth year, a male dummy and a full set of interactions between the birth year and gender dummies. Additionally, every specification includes the first 10 principle components of the full matrix of genetic data and controls for parental education (years of paternal and maternal education and dummies indicating missing values for each). Some regressions include measures of childhood SES and controls for own education, as indicated.

Appendix Table S10: Results Using Alternate Polygenic Scores (Continued from Previous Page)

Dep Var:	(1) Years of Educ.	(2) At Least H.S.	(3) At Least H.S.	(4) At Least Coll.	(5) At Least Coll.	(6) log Earn.	(7) log Earn.	(8) log Earn.
Panel F: LD Pred Score from Reitveld et al. (2013), N = 126,559								
Sample: 2006 and 2008 Waves of HRS Genetics Sample								
EA Score	0.297***	0.020	0.022	0.015	0.017	0.014	0.012	-0.004
	(0.038)	(0.013)	(0.014)	(0.010)	(0.012)	(0.009)	(0.010)	(0.006)
High Father's Inc.		0.063***		0.082***				
		(0.018)		(0.014)				
Score × High Fath. Inc.		-0.008		0.041***				
		(0.012)		(0.012)				
Family Well Off			0.072***		0.023			
			(0.018)		(0.015)			
Score × Fam. Well Off			-0.014		0.030**			
			(0.014)		(0.012)			
Score × At Least Coll.							0.019	
							(0.020)	
Score × Post 1980								0.033***
								(0.013)
Obs.	8537	6750	8387	6750	8387	96721	96510	96510
R^2	0.330	0.246	0.234	0.220	0.196	0.189	0.193	0.204
Panel G: All SNPs Score from Reitveld et al. (2013), N = 126,559								
Sample: 2006 and 2008 Waves of HRS Genetics Sample								
EA Score	0.287***	0.022*	0.025*	0.018*	0.023*	0.012	0.009	-0.005
	(0.038)	(0.013)	(0.014)	(0.010)	(0.013)	(0.009)	(0.010)	(0.006)
High Father's Inc.		0.063***		0.083***				
		(0.018)		(0.014)				
Score × High Fath. Inc.		-0.008		0.042***				
		(0.012)		(0.012)				
Family Well Off			0.073***		0.023			
			(0.018)		(0.015)			
Score × Fam. Well Off			-0.013		0.027**			
			(0.014)		(0.012)			
Score × At Least Coll.							0.020	
							(0.020)	
Score × Post 1980								0.028**
								(0.013)
Obs.	8537	6750	8387	6750	8387	96721	96510	96510
R^2	0.330	0.246	0.234	0.220	0.196	0.188	0.193	0.203

Regressions relating different versions of the EA score to various educational and labor outcomes examined in the main text. Regressions also include a full set of dummy variables for birth year, a male dummy and a full set of interactions between the birth year and gender dummies. Additionally, every specification includes the first 10 principle components of the full matrix of genetic data and controls for parental education (years of paternal and maternal education and dummies indicating missing values for each). Some regressions include measures of childhood SES and controls for own education, as indicated.

B.6 Further Details on Top-Coding and Alternative Income Measures

One limitation of the SSA earnings data is that they are subject to fairly heavy rates of top-coding, and the severity of the top coding has changed over time. The maximum amount of earnings subject to social security taxes dictates the level of top-coding in the SSA earnings data, and this has changed with reforms to the social security system. For example, while the taxable maximum stood at $3,000 in 1950 ($27,144 in 2010 dollars), it grew to $7,800 ($43,836) in 1970, $51,300 ($85,587) in 1990, and $106,800 in 2010 (Whitman and Shoffner, 2011). Panel A of Figure S2 plots the evolution of the fraction of individuals who report incomes that are subject to the top code, both using the SSA earnings data for our sample, and using data from the March Current Population Survey. Top Coding rates were quite severe in earlier decades and exceeded 60 percent for most years before 1980. The top coding rates plummeted with changes at the end of the 1970s. Starting at levels just over 20 percent, the top coding rate has declined slowly and steadily since 1980.

The pattern of top-coding observed in Panel A of Figure S2 raises questions about how to interpret some of our findings linking the EA score and log earnings. Specifically, in Panel B of Table 5, we find that the relationship between the EA score and earnings grew after 1980. One interpretation of this result is that the economic environment shifted over this time period to increasingly reward the kinds of traits possessed by people with high values of the EA score. However, this pattern could also simply reflect changes in the top coding scheme in earnings, if the relationship between the EA score and earnings is primarily located in the upper half of the earnings distribution. To shed a bit more light on this, Panel B of Figure S2 presents nonparametric local polynomial plots of the relationship between calendar year and log earnings residuals for each tercile of the EA score distribution. The residuals here arise from a regression of log earnings on our basic control set and controls for parental and own education. We find that residual earnings differences between EA terciles (especially the top and bottom tercile) tend to fan out continuously after 1980. This suggests that the changes in top coding do not offer a complete explanation for our results, since the fraction of the population subject to top coding declined quite slowly after 1980, while differences in earnings by EA tercile accelerated.

Another way of assessing the impact of top coding is to compare earnings results from the SSA data with self-reported earnings measures asked by the HRS. Table S11 presents comparable specifications using both the HRS data and the SSA data. Column (1) regresses log earnings on the EA score and our basic controls, without controls for own or parental education. Column (2) regresses log earnings, our basic controls, and controls for own and parental education. Column (3) then adds an interaction between the EA score and an indicator for a college degree to the previous specification, along with interactions between the principal components and the college variable. Panel A examines the log of self-reported earned income in the HRS as the dependent variable and restricts the sample to men between the ages of 50-64 who work at least 20 hours per week. Panels B uses the log of SSA earnings as the dependent variable, but restricts the sample to men earning more than $10,000 (real 2010 dollars) during or after the year 1992 (to match the HRS). The results across both specifications tend to be quite similar. The point estimates in Column (1) are nearly identical, and we find evidence of a return to the EA score above and beyond education in both samples. This suggests that the extent of top coding observed in the 1980s and beyond is unlike to substantially influence our results using the SSA data for that time period.

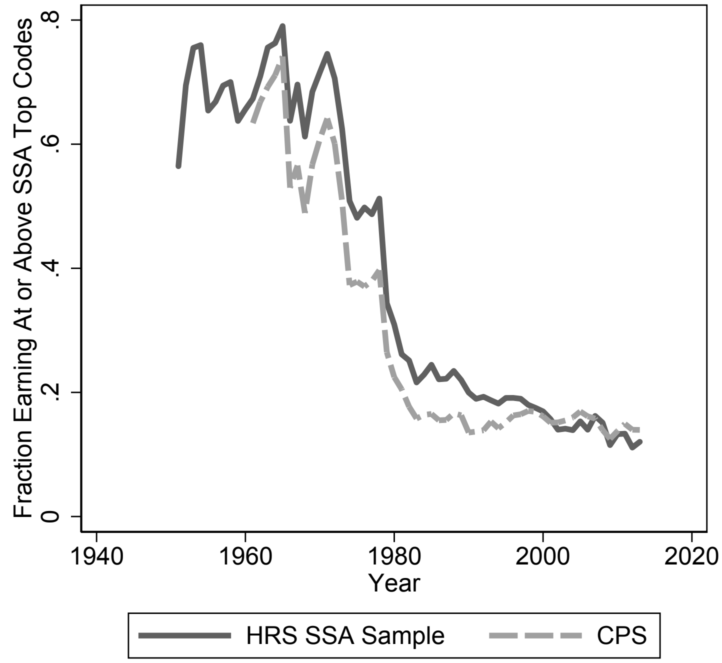
Another difference between the SSA data and self-reports in the HRS is that the SSA data reports earnings totals for the year, but not hours worked, and thus does not permit an analysis of wages. Questions on the number of hours worked per week in the HRS allow one to construct a measurement of the log wage for each worker. In Panel C of Table S11, we repeat the specifications in Panel A, but now use the log wage instead of log income in the HRS. We find similar results whether using income or the wage in the HRS, suggesting that the patterns we observe are unlikely to be due to changes in labor supply. One difference is that we find a significant interaction between the EA score and the College indicator in the HRS sample for the log Wage (Column 3), while we do not find such an interaction in earnings using either data source.

Appendix Table S11: Polygenic Score and Earnings in the HRS and SSA Data

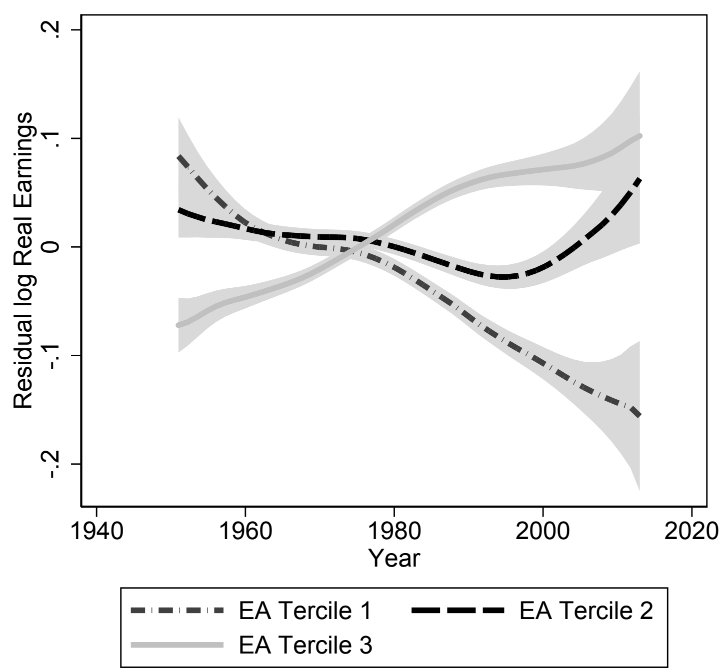
	(1)	(2)	(3)
Panel A: log of Self-Reported Earnings in HRS			
EA Score	0.143***	0.043**	0.025
	(0.018)	(0.018)	(0.020)
EA Score x College			0.040
			(0.037)
Obs.	8479	8479	8443
R^2	0.067	0.156	0.160
Panel B: log of Earnings in SSA Data			
EA Score	0.142***	0.056***	0.036*
	(0.018)	(0.019)	(0.022)
EA Score x College			0.046
			(0.039)
Obs.	16208	16208	16148
R^2	0.082	0.170	0.173
Panel C: log of Self-Reported Wages in HRS			
EA Score	0.130***	0.029*	0.002
	(0.016)	(0.015)	(0.018)
EA3ScorexAtLstCollege			0.067**
			(0.032)
Obs.	7142	7142	7114
R^2	0.078	0.216	0.222

Regressions relating different measures of earnings to the EA score and completed education (college degree). The sample is limited to males. All regressions include a full set of dummy variables for birth year. Additionally, every specification includes the first 10 principle components of the full matrix of genetic data.

Panel A: Fraction of Earnings Observations Above SSA Top Codes



Panel B: Residual Earnings Over Time by EA Tercile



Appendix Figure S2: Top Coding and Residual Earnings by EA Tercile. Panel B presents non-parametric (local polynomial) estimation relating year and earnings separately for terciles of the EA score distribution. Shaded areas depict 95 percent confidence intervals.

B.7 The EA Score and Labor Supply

Panels A and B of Table S12 provide estimated associations between the EA score and work status and retirement, respectively. As with wages, only men are included in these regressions because of the substantial amount of selection governing female labor force participation for these cohorts. Panel A investigates the relationship between the EA score and a binary variable indicating whether or not the respondent is working for pay. Column (1) reports results when the only controls are the principal components of the genetic data, a full set of dummy variables for age, dummy variables for each birth year, and dummy variables for each calendar year. For ease of exposition, we use a linear probability model. The coefficient in Column (1) of 0.056 suggests that a one standard deviation increase in the EA score is associated with a 5.6 percentage point increase in the probability of working. In Column (2), we add controls for own education (years of schooling and a complete set of degree dummies) as well as parental education. Adding these controls causes the coefficient on EA Score to fall to 0.036, though it remains statistically significant. In Column (3), we also allow for an interaction between EA score and a dummy for obtaining at least a college degree to allow for possible complementarities between schooling and genetic factors that promote education. We find no evidence of such complementarities for this measure of work.

In Panel B of Table S12, we consider the discrete-time hazard of retiring given employment in the previous wave of the HRS. We restrict the sample to those who were not retired and who were working for pay in the previous HRS wave. We regress a binary outcome for whether or not an individual declares that they are currently retired onto the same sets of regressors used in the wage equations. The estimated coefficient on the EA score is -0.013 in the first two specifications and -0.015 in the third. The magnitude of this association is particularly striking. The probability of retirement in any year of our sample is about 11 percent. The estimated associations here suggest that a one standard deviation change in the EA score is associated with a roughly 1.3 percentage point reduction in retirement probability, even after controlling for own and parental education.[71] This represents an association that is more than 10 percent of the average retirement rate in our sample.

[71] An extension would look at retirement more carefully, taking into account that a discrete time hazard may overlook important non-linearities in retirement probability as individuals age.

Appendix Table S12: Polygenic Score and Labor Supply Outcomes

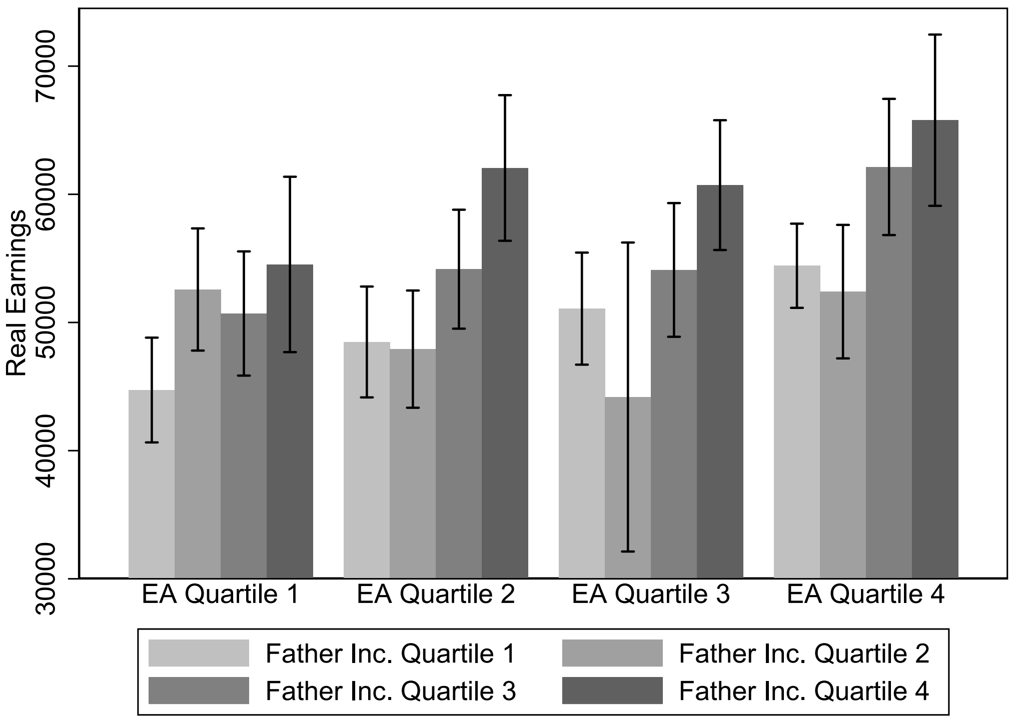
Panel A: Dep. Var Work For Pay	(1)	(2)	(3)
EA Score	0.056***	0.036***	0.040***
	(0.008)	(0.008)	(0.011)
EA Score x College			-0.020
			(0.015)
Obs.	13744	13744	13695
R^2	0.093	0.115	0.119
Educ. Controls	N	Y	Y
Parent Controls	N	Y	Y

Panel B: Dep. Var Retired	(1)	(2)	(3)
EA Score	-0.013***	-0.013***	-0.015***
	(0.004)	(0.004)	(0.005)
EA Score x College			0.004
			(0.009)
Obs.	8218	8218	8188
R^2	0.095	0.100	0.101
Educ. Controls	N	Y	Y
Parent Controls	N	Y	Y

Regressions relating the EA score to labor market outcomes. In Panel A, the dependent variable is employment (working for pay). In Panel B, the dependent variable is retirement and conditions on not being retired in the previous period. All regressions include the first 10 principle components of the full matrix of genetic data along with a full set of dummy variables for birth year, calendar year and age. Because of collinearity a subset of these dummies is dropped. The specifications in Columns 2 and 3 include controls for parental education (years of paternal and maternal education and dummies indicating missing values for each) and own education (years of schooling and a full set of completed degree dummies). The specification in Column 3 includes as additional controls interactions between the principle components and an indicator for earning at least a college degree. The sample in Panel A is restricted to men between the ages of 50 and 64. The sample in Panel B is restricted to men between the ages of 50 and 64 who worked for pay in the last period and were not retired in the last period.

B.8 Father's Income, the EA Score and Earnings

Figure S3 repeats the analysis conducted to generate Figure 5, but uses average real earnings as the outcome variable. This exercise is restricted to include only the men in the baseline earnings sample. Once again, we assign each individual to a quartile of the EA score distribution and a quartile of the father's income distribution, generating 16 possible combinations of SES and EA quartile groupings. Figure S3 shows average annual earnings (ages 30-50) for each quartile combination. We find that average adult earnings generally rise in both the EA quartile and the father's income quartile. Within each EA score quartile, we can reject the null hypothesis that average earnings are equal for individuals in quartile 4 (Q4) and quartile 1 (Q2) of the father's income distribution (p-val<0.05 in all cases). We do not find consistent evidence that the average earnings gap between Q4 and Q1 of the father's income distribution rises as we move across EA quartiles. However, there does seem to be a pattern if we instead look at the difference in average earnings between Q4 and Q2 of the father's income distribution. For individuals in the lowest EA score quartile, we cannot reject the null hypothesis that average earnings are equal for individuals in Q4 and Q2 of the father's income distribution. However, in all of the higher EA score quartiles, we find a statistically significant difference in average earnings between Q4 and Q2 of the father's income distribution. The confidence intervals indicate that the relationships are noisier in general than in the case of the degree completion. Still, Figure S3 suggests that the interactions between the EA score and father's income shape earnings outcomes, though perhaps in a more complicated way than for educational outcomes.



Appendix Figure S3: Average Earnings (Age 30-50) by Father's Income and EA Score. Bars are plotted with 95 percent confidence intervals.

C Bias in Estimated Coefficients

In this appendix, we discuss potential biases to parameter estimates. A key problem is that genetic endowments can affect returns to human capital investments, but also drive these investments. One reason is that parents who provide advantageous genetic material may also be more likely to invest in their children. Further problems arise since we do not measure human capital investments directly. Instead, we proxy for them using various measures of parent SES. These proxies may be systematically mis-measured. Here, we explore the consequences for parameter estimates.

First, suppose we want to relate a continuous economic outcome y_i to a polygenetic score and denoted G_i, and a continuous investment in human capital I_i

$$y_i = G_i\phi_1 + I_i\phi_2 + (G_i \times I_i)\phi_3 + \epsilon_i \tag{4}$$

In this equation, ϵ_i is an *iid* disturbance. ϕ_3 is of particular policy relevance as it captures whether genetic endowments and investments are complements ($\phi_3 > 0$) or substitutes ($\phi_3 < 0$).

There are two difficulties in estimating equation (4) which we emphasize. First, we proxy for investments using family SES, which we denote S_i. Investments may therefore be systematically mis-measured as follows:

$$I_i = S_i\rho_1 + G_i\rho_2 + G_i^P\rho_3 + \nu_i \tag{5}$$

The investment equation captures three features of our setting. First, family SES is an imperfect measurement of human capital investments. Second, the measurement error may be systematically related to genotype G_i. For example, if $\rho_2 > 0$, then parent SES systematically underestimates investments in children with high polygenic scores. Finally, parents with stronger genetic endowments, which we denote G_i^P, may also provide better environments for their children even after we have controlled for parent SES.

Another feature of our setting is that G_i reflects parent genetic endowments, which we denote G_i^P. We capture this with the following equation:

$$G_i = G_i^P\alpha + e_i \tag{6}$$

Notice that investments and SES, though they may be correlated with unobservable variables that affect outcomes, cannot influence an individual's polygenetic score. This will prove helpful for inference on how innate abilities interact with investments. In particular, we are interested in the structural relationship expressed in equation (4). We rewrite it, but substituting in the investment relationship from equation (5) to obtain an estimable expression:

$$\begin{aligned} y_i &= G_i\phi_1 + [S_i\rho_1 + G_i\rho_2 + G_i^P\rho_3 + \nu_i]\phi_2 + (G_i \times [S_i\rho_1 + G_i\rho_2 + G_i^P\rho_3 + \nu_i])\phi_3 + \epsilon_i \\ &= G_i(\phi_1 + \rho_2\phi_2) + S_i\rho_1\phi_2 + (G_i \times S_i)\rho_1\phi_3 \\ &+ G_i^P\rho_3\phi_2 + G_i^2\rho_2\phi_3 + G_iG_i^P\rho_3\phi_3 + \nu_i\phi_2 + G_i\nu_i\phi_3 + \epsilon_i \end{aligned} \tag{7}$$

Next, recognize that $G_i^P = \frac{G_i - e_i}{\alpha}$. Thus, we can rewrite the outcome as:

$$\begin{aligned} y_i &= G_i(\phi_1 + \rho_2\phi_2) + S_i\rho_1\phi_2 + (G_i \times S_i)\rho_1\phi_3 \\ &+ G_i\frac{\rho_3\phi_2}{\alpha} + G_i^2\rho_2\phi_3 + G_i^2\frac{\rho_3\phi_3}{\alpha} + \nu_i\phi_2 + G_i\nu_i\phi_3 + \epsilon_i \\ &- e_i\frac{\rho_3\phi_2}{\alpha} - G_ie_i\frac{\rho_3\phi_3}{\alpha} \end{aligned} \tag{8}$$

Simplifying, leads us to the following estimable expression:

$$\begin{aligned} y_i &= G_i\kappa_1 + S_i\kappa_2 + (G_i \times S_i)\kappa_3 + G_i^2\kappa_4 + \xi_i \\ \kappa_1 &= \phi_1 + \rho_2\phi_2 + \frac{\rho_3\phi_2}{\alpha} \\ \kappa_2 &= \rho_2\phi_2 \\ \kappa_3 &= \rho_1\phi_3 \\ \kappa_4 &= \rho_2\phi_3 + \frac{\rho_3\phi_3}{\alpha} \\ \xi_i &= \nu_i\phi_2 - e_i\frac{\rho_3\phi_2}{\alpha} + G_i\nu_i\phi_3 - G_ie_i\frac{\rho_3\phi_3}{\alpha} + \epsilon_i \end{aligned} \tag{9}$$

The final equation is similar to the type of equations we estimate. Estimated parameters are related to the parameters of interest in equation (4). To simplify the discussion, we assume that $\phi_1 > 0$ (the impact of G_i on y_i is positive) and $\phi_2 > 0$ (the impact of investments on y_i are positive). We also maintain the assumptions that $\rho_1 > 0$ (higher SES translates to higher investments) and $\rho_3 > 0$ (parents with more advantageous genetic endowments invest more in their children even after we have controlled for SES). Finally, we recognize that parent and child genetic endowments are positively correlated ($\alpha > 0$).

The following are true.

1. We over-estimate the positive impact of G_i on y_i ($\kappa_1 > \phi_1$) if $\rho_2\phi_2 + \frac{\rho_3\phi_2}{\alpha} > 0$. This holds if $\rho_2 \geq 0$. If $\rho_2 < 0$, the direction of bias cannot be signed.

2. We over-estimate ϕ_2 if $\rho_2 > 1$. If $\rho_2 < 1$, then we under-estimate it.

3. As long as SES predicts actual investments ($\rho_1 > 0$), the sign of κ_3 is the same as the

sign of ϕ_3. In other words, we estimate the correct sign of ϕ_3, which governs whether the polygenic score and investments in human capital are complements or substitutes. This is important as we are particularly interested in understanding how heterogeneity in genetic endowments is mitigated human capital investments.

4. The estimating equations should control for a second-order polynomial in genetic score. This controls for how genetic score affects y_i both directly and through its impact on mis-measured investments.

5. Estimating equations should take account of heteroskedasticity since the variance of ξ_i is a function of G_i.

One of the key results of this exercise is to show that we can identify the correct sign of ϕ_3, which governs interactions between endowments and investments, which are measured using child SES. We obtain the correct sign even though SES, genes and parent genes can all affect investments. Here, we show that our ability to identify the sign of ϕ_3 rests on the fact that the polygenic score is not affected by investments. Suppose instead that we use a traditional proxy for ability or cognition endowments, such as cognitive test scores, which are affected by investments. In this case, we can no longer identify the sign of ϕ_3. We illustrate this point with a simpler version of the model. Once again, our goal is to estimate the parameters in equation (4). We add two more equations to the system: a simplified version of the investment equation and an equation relating cognitive test scores (denoted C_i) to genes and investments. The investment equation is

$$I_i = S_i\gamma_1 + G_i\gamma_2 + \nu_i^I \tag{10}$$

Here, we have dropped parent genes G_i^P for ease of exposition. Cognitive test scores are explained by:

$$C_i = I_i\alpha_1 + G_i\alpha_2 + \nu_i^C \tag{11}$$

This means that a cognitive test score is a function of investments I_i and genes G_i. The next step is to solve for G_i and I_i as functions of observable variables S_i and C_i, which are then substituted into equation (4) to obtain an estimable expression. The estimable expression is similar to equation (4), but in place of G_i, we have C_i:

$$y_i = C_i\delta_1 + S_i\delta_2 + (C_i \times S_i)\delta_3 + \nu_i^Y \tag{12}$$

It can be shown that $sign(\delta_3) = sign(\phi_3)$ if $\frac{\alpha_2}{\alpha_1} + \gamma_2 > 2\gamma_1$. The interpretation is that if factors other than genetics are important in explaining C_i, we are more likely to mis-estimate the sign of ϕ_3.

D Cognitive Test Scores

A natural question to ask is how the polygenic score relates to more typical proxies for ability, such as cognitive test scores. Fortunately, we are able to compare cognitive test scores to the polygenic score. The HRS features a number of items related to cognition, including two memory tests, two simple math exercises, and eight general knowledge questions, which have been used in prior literature as a measure of cognition (McArdle, Smith, and Willis, 2009).

Each memory test is scored out of ten, for a total of twenty possible points. Subjects' memory was tested using a list of ten common nouns. They were asked to recall as many of the nouns as possible both immediately after the list was read and after a predetermined set of survey questions (or about five minutes). The math exercises account for seven points: two awarded for correctly counting back from 20 to 10 on the first try (or one on a second try), and one each for 5 rounds of correctly subtracting 7 from 100. Eight points are scored by correctly naming the day of the week, date, month, and year, the objects "people usually use to cut paper" and the "kind of prickly plant that grows in the desert", and the sitting President and Vice President.

Our specific measure of cognitive functioning comes from the *Imputation of Cognitive Functioning Measures* file of the HRS. Specifically, we use the imputed "Total Cognition Summary Score" for each wave. This score aggregates the previously mentioned cognition measures and takes values between 0-35. To remove the effects of age and gender, we regress all observations of the total cognition score for genetic Europeans on a male dummy, a quartic in age, and an interaction between male and the quartic age terms. We then average the residuals for each individual and standardize this average so that it has zero mean and a standard deviation of one.

We plot the distribution of the cognition score in Figure S4. Similar to the EA score (refer back to Figure 2), the cognition score is approximately normally distributed. The correlation between cognition score and EA score is positive but modest ($\rho = 0.23$). A scatter plot indicates this weak positive correlation (Figure S5).

We next assess whether the EA score and the cognition score exhibit similar relationships with educational attainment. Table S13 presents specifications that add the cognition score to our basic set of regressions explaining educational attainment from Table 2. Both the EA score and the cognition score exhibit a substantial, highly significant statistical relationship with educational attainment. Since the two scores are somewhat correlated, the coefficient on the EA score does drop somewhat when the cognition score is added. In the full specification with all SES controls, the coefficient on the EA score is 0.458 compared to 0.587 in the same specification without the cognition score (compare the coefficient attached to EA score in Column (5) of Table 2 from the main text with the analogous coefficient in Column (5) of Table S13 in this appendix). The relationship between the cognition score and education is sizable, with a one standard deviation increase in the cognition score being associated with an increase of educational attainment of 0.702 years.

In Table S14, we re-estimate our specifications that interact the EA score with SES measures in predicting a degree at or above five different thresholds. Here we also add the cognition score, and an interaction between the cognition score and the SES measure in each specification. Adding the cognition interactions does not change our conclusions about the pattern and significant of interactions between the EA score and childhood SES.

Finally, Table S15 repeats some key earnings specifications while also controlling for the cognition score and interactions between the cognition score and other regressors. In particular, the EA score remains a significant predictor of earnings even after controlling for cognition and education. Interestingly, while we find evidence that the association between earnings and the EA score rose after 1980, we find no evidence of this interaction with the cognition score. This suggests that the two measures may reflect distinct bundles of traits or skills.

Appendix Table S13: Polygenic Score, Cognition Score, and Educational Attainment

	(1)	(2)	(3)	(4)	(5)
EA Score	0.615***	0.478***	0.475***	0.458***	0.458***
	(0.045)	(0.043)	(0.042)	(0.044)	(0.031)
Cog. Score	0.914***	0.727***	0.726***	0.710***	0.702***
	(0.060)	(0.055)	(0.056)	(0.053)	(0.035)
Father Educ		0.126***	0.126***	0.090***	0.094***
		(0.013)	(0.013)	(0.015)	(0.012)
Mother Educ		0.136***	0.135***	0.117***	0.119***
		(0.015)	(0.015)	(0.015)	(0.014)
Obs.	8470	8470	8470	8470	8470
R^2	0.346	0.414	0.415	0.431	0.568
Child SES Measures	N	N	Y	Y	Y
Child Region	N	N	N	Y	Y
Religion	N	N	N	N	Y

Regressions relating educational attainment (years) to the EA score and the cognition score. All regressions include a full set of dummy variables for birth year, a male dummy and a full set of interactions between the birth year and gender dummies. All specifications include the first 10 principle components of the full matrix of genetic data as controls. Some specifications include controls for parental education, childhood health, childhood SES measures, region during childhood and religion, as indicated.

Appendix Table S14: Polygenic Score, Cognition Score, and Interactions with SES

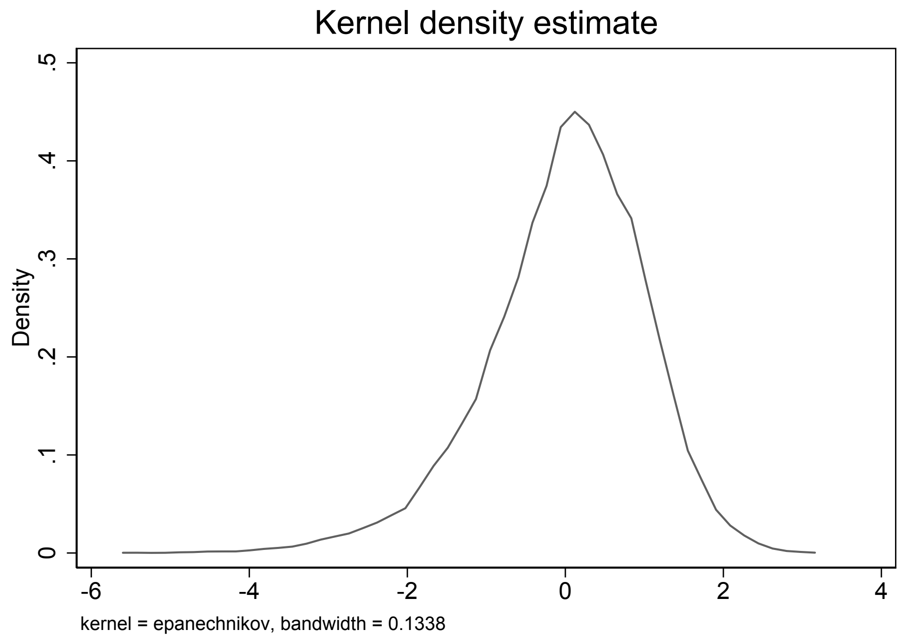
Dep Var: At Least	(1) H.S. Equiv	(2) High School	(3) Two Yr.	(4) College	(5) Grad
Panel A: SES Measure - Father Occ. Income					
High SES	0.038***	0.048***	0.065***	0.072***	0.028***
	(0.010)	(0.011)	(0.013)	(0.012)	(0.008)
EA Score	0.041***	0.041***	0.088***	0.078***	0.017**
	(0.013)	(0.015)	(0.014)	(0.012)	(0.009)
EA Score × High SES	-0.014	-0.017	0.040***	0.053***	0.020**
	(0.011)	(0.013)	(0.013)	(0.012)	(0.009)
Obs.	6705	6705	6705	6705	6705
R^2	0.334	0.310	0.283	0.287	0.138
Panel B: SES Measure - Family Well Off					
High SES	0.038***	0.059***	0.044***	0.055***	0.018**
	(0.013)	(0.014)	(0.014)	(0.013)	(0.009)
EA Score	0.051***	0.080***	0.034**	0.031**	0.005
	(0.013)	(0.015)	(0.014)	(0.012)	(0.008)
EA Score × High SES	-0.005	-0.023*	0.049***	0.057***	0.028***
	(0.012)	(0.014)	(0.013)	(0.011)	(0.008)
Obs.	8321	8321	8321	8321	8321
R^2	0.312	0.300	0.259	0.271	0.137
Panel C: SES Measure - Move or Asked for Help					
High SES	0.029**	0.054***	0.085***	0.103***	0.034***
	(0.012)	(0.014)	(0.015)	(0.013)	(0.010)
EA Score	0.028**	0.050***	0.016	0.026**	0.003
	(0.014)	(0.015)	(0.014)	(0.012)	(0.008)
EA Score × High SES	0.005	-0.018	-0.003	-0.006	0.008
	(0.012)	(0.014)	(0.014)	(0.012)	(0.009)
Obs.	8298	8298	8298	8298	8298
R^2	0.309	0.294	0.256	0.268	0.136
Panel D: SES Measure - Father Unemployed					
High SES	0.043***	0.058***	0.059***	0.083***	0.030***
	(0.011)	(0.013)	(0.016)	(0.013)	(0.010)
EA Score	0.011	0.029**	0.023	0.030**	0.009
	(0.013)	(0.014)	(0.014)	(0.012)	(0.008)
EA Score × High SES	-0.014	-0.023*	0.029**	0.019	0.012
	(0.011)	(0.013)	(0.014)	(0.012)	(0.009)
Obs.	8336	8336	8336	8336	8336
R^2	0.306	0.291	0.254	0.266	0.134

Regressions relating educational attainment categories to the EA score, the cognition score and childhood SES along with interactions between the EA score and high SES. Regressions also include a full set of dummy variables for birth year, a male dummy and a full set of interactions between the birth year and gender dummies. Additionally, every specification includes the first 10 principle components of the full matrix of genetic data and controls for parental education (years of paternal and maternal education and dummies indicating missing values for each). Every specification includes the cognition score and an interaction between the cognition score and the High SES indicator.

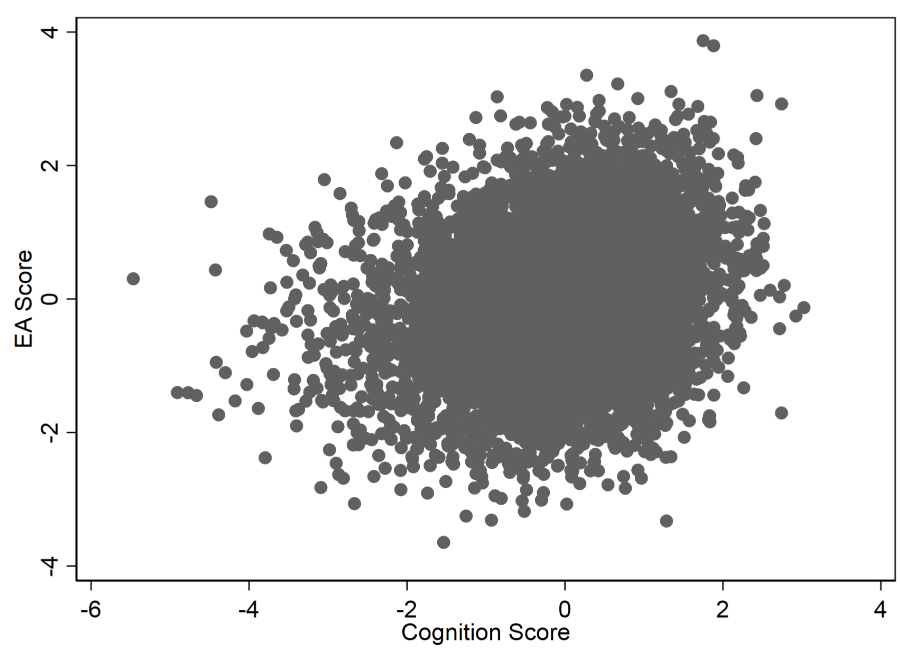
Appendix Table S15: Polygenic Score, Cognitive Score, and Earnings

Dep Var.: log SSA Earnings				
Basic Specifications	(1)	(2)	(3)	(4)
EA Score	0.057***	0.029***	0.023**	0.007
	(0.009)	(0.009)	(0.010)	(0.007)
EA Score × College			0.011	
			(0.020)	
EA Score × Post 1980				0.039***
				(0.012)
Cog. Score	0.088***	0.042***	0.059***	0.031***
	(0.010)	(0.010)	(0.011)	(0.008)
Cog. Score × College			-0.060**	
			(0.025)	
Cog. Score × Post 1980				0.020
				(0.013)
College × Post 1980				0.249***
				(0.030)
Obs.	95945	95945	95734	95734
R^2	0.168	0.195	0.200	0.210
Age Group	25-64	25-64	25-64	25-64
Period	All Years	All Years	All Years	All Years
Educ. Controls	N	Y	Y	Y
Parent Controls	N	Y	Y	Y

Regressions relating the EA score and the cognition score to log earnings. In all specifications, we restrict the sample to earnings records for men between the ages of 25 and 64 over the years 1951-2013 in which the respondent earns more than $10,000 in real 2010 dollars. In Column (4), the sample is narrowed to cover person-years in which respondents are aged between 40 and 64. In Columns (5), the sample again includes all ages 25-64, but is now restricted to years 1980-2013. The dependent variable is the the log of real earnings. All regressions include the first 10 principle components of the full matrix of genetic data along with a full set of dummy variables for birth year, calendar year and age. As noted in the table, the specifications in Columns (2)-(4) include controls for parental education (years of paternal and maternal education and dummies indicating missing values for each) and own education (years of schooling and a full set of completed degree dummies). Standard errors in all specifications are clustered at the person level.



Appendix Figure S4: Distribution of cognitive test scores (cognition score), which is the standardized individual-level average residual from a regression of cognition on age



Appendix Figure S5: Scatter Plot by Individual of EA Score and Cognition Score.

E Construction of Weights and Multiple Hypothesis Testing

E.1 Inverse Probability Weights

To create weights, we first estimate a probit model predicting inclusion in the 2006 or 2008 genetic sample for all HRS respondents as a function of birth year dummies, region of birth dummies, completed degree dummies, years of schooling, father's education, mother's education, separate dummy variables for missing father's or mother's education, and a male dummy. We use the estimates of this model to generate a predicted probability of sample inclusion conditional on these observables:, $\widehat{\pi}_i = \widehat{P}(\ In\ Sample \mid X_i)$. Let ω_i represent the cross-sectional HRS sampling weight associated with individual i. We multiply these weights by the factor $(1/\widehat{\pi}_i)$ to adjust for non-random selection into the genotyped sample. That is, the sampling weights applied to our sample are $(\omega_i/\widehat{\pi}_i)$. The cross-sectional respondent-level weight generated by the HRS changes across waves as the sample is expanded or reweighted. A major change occurred in 2004, when the weights were post-stratified to match the American Community Survey instead of the smaller March CPS (Staff, 2015). Given this change, we set ω_i equal to the first non-zero cross-sectional sampling weight provided in or after the 2004 wave. For a small number of individuals without any non-zero weight matching this criterion, we use the first non-missing household-level weight provided in or after the 2004 wave.

E.2 Multiple Hypothesis Testing

Given the fairly large number of hypotheses tested in this paper, we now consider formal corrections in the p-values of our results to address multiple comparisons. In particular, we split our results into two families of new hypotheses: (i) Interactions between the EA score and SES measures in predicting completed degrees; and (ii) Associations between the EA score and labor market outcomes above and beyond completed schooling. Figure 6 summarizes our results for Family 1, which consists of 20 hypothesis tests, based on the use of four distinct SES measures each interacted with the EA score in predicting five different degree outcomes. Family 2 consists of regression results on earnings as well as job tasks. Family 2 includes the regression on log earnings on the EA score after controlling for education, the regression of log earnings on the EA score and an interaction between the score and the college dummy variable, the regression of the log earnings on the EA score and an interaction between the score and a post-1980 indicator, and the regression of log earnings on the EA score and an interaction between the score and a post-1942 birth year indicator. In addition to these four earnings hypotheses, we also include ten hypotheses related to job tasks. In addition to the five hypotheses contained in Table 6, we also include five more specifications analogous to those in 6, but using dummies for above median values of the job tasks as the dependent variable.[72]

We correct for multiple comparisons in two ways. First, we apply a Bonferroni correction by multiplying the p-values by the number of hypotheses tested. We do this both within the two families separately (20 hypotheses and 14 hypotheses, respectively), and for the combined family of all hypotheses (34 hypotheses). We also correct for multiple comparisons using the bootstrap procedure developed by Romano and Wolf (2005) and elaborated in Romano and Wolf (2016). We again apply this procedure separate to each family, and we also apply the procedure to the meta-family of all 34 hypotheses.

Table S16 lists our 34 hypotheses and indicates the dependent variable and coefficient of interest involved in the test. We report the original p-values for each test, as well as the Bonferroni and Romano-Wolf corrected p-values. We find strong evidence for interactions between the EA score and at least two SES measures (Father's Income and Family Well Off) in predicting a college degree, even when applying the Bonferroni correction. The negative interaction between the EA score and the Family Well Off in predicting the high school outcome survives as marginally significant in the within-family corrections. The significance of the association between log earnings and the EA score (conditional on education) survives all corrections, and we find a significant p-value for the hypothesis on the interaction between the EA score and the post-1980 indicator in predicting earnings (p-value<0.10 in all corrections and p-value<0.05 in the within-family corrections). The result relating the EA score to the non-routine analytic task intensity (Task 1) survives as marginally significant in the omnibus corrections (p-value<0.10), and significant in the within-family corrections (p-value<0.05).

[72] In a previous version of the paper, we used the median-based measure, but switched to using standardized job tasks in this draft. We include all of these specifications in this family for the purpose of corrections for multiple comparisons.

Appendix Table S16: Corrections for Multiple Hypothesis Testing

Hyp. Num.	Dep. Var.	Coeff.	Original $p-$value	Bonferroni All Hyp.	Bonferroni in Family	Romano-Wolf All Hyp.	Romano-Wolf in Family
Family 1: SES Interactions							
(1)	HS Equiv.	EA Score × Fam Well Off	0.139	1.000	1.000	0.823	0.522
(2)	HS	EA Score × Fam Well Off	0.005	0.166	0.098	0.160	0.101
(3)	Two Yr.	EA Score × Fam Well Off	1.2e-05	4.24e-04	2.49e-04	0.001	0.001
(4)	College	EA Score × Fam Well Off	7.9e-08	2.7e-06	1.6e-06	0.001	0.001
(5)	Grad	EA Score × Fam Well Off	2.95e-04	0.010	0.006	0.018	0.011
(6)	HS Equiv.	EA Score × High Fath. Inc	0.011	0.380	0.223	0.270	0.178
(7)	HS	EA Score × High Fath. Inc	0.036	1.000	0.713	0.508	0.332
(8)	Two Yr.	EA Score × High Fath. Inc	0.002	0.058	0.034	0.087	0.053
(9)	College	EA Score × High Fath. Inc	5.6e-06	1.91e-04	1.12e-04	0.001	0.001
(10)	Grad	EA Score × High Fath. Inc	0.056	1.000	1.000	0.616	0.426
(11)	HS Equiv.	EA Score × Nev. Move/Ask	0.864	1.000	1.000	0.999	0.904
(12)	HS	EA Score × Nev. Move/Ask	0.036	1.000	0.714	0.508	0.332
(13)	Two Yr.	EA Score × Nev. Move/Ask	0.570	1.000	1.000	0.998	0.904
(14)	College	EA Score × Nev. Move/Ask	0.667	1.000	1.000	0.999	0.904
(15)	Grad	EA Score × Nev. Move/Ask	0.169	1.000	1.000	0.852	0.522
(16)	HS Equiv.	EA Score × Nev. Unemp.	0.094	1.000	1.000	0.756	0.510
(17)	HS	EA Score × Nev. Unemp.	0.017	0.571	0.336	0.337	0.234
(18)	Two Yr.	EA Score × Nev. Unemp.	0.014	0.486	0.286	0.321	0.214
(19)	College	EA Score × Nev. Unemp.	0.025	0.845	0.497	0.432	0.285
(20)	Grad	EA Score × Nev. Unemp.	0.100	1.000	1.000	0.756	0.510
Family 2: Earnings and Tasks							
(21)	log. Earnings	EA Score	0.001	0.017	0.007	0.033	0.016
(22)	log. Earnings	EA Score × College	0.428	1.000	1.000	0.987	0.955
(23)	log. Earnings	EA Score × Post 1980	0.002	0.077	0.032	0.095	0.044
(24)	log. Earnings	EA Score × BY > 1942	0.650	1.000	1.000	0.999	0.988
(25)	> Med. Task 1	EA Score	0.001	0.023	0.010	0.040	0.020
(26)	> Med. Task 2	EA Score	0.006	0.221	0.091	0.192	0.080
(27)	> Med. Task 3	EA Score	0.634	1.000	1.000	0.999	0.988
(28)	> Med. Task 4	EA Score	0.653	1.000	1.000	0.999	0.988
(29)	> Med. Task 5	EA Score	0.958	1.000	1.000	0.999	0.988
(30)	Std. Task 1	EA Score	0.002	0.062	0.026	0.087	0.039
(31)	Std. Task 2	EA Score	0.015	0.503	0.207	0.325	0.144
(32)	Std. Task 3	EA Score	0.367	1.000	1.000	0.982	0.937
(33)	Std. Task 4	EA Score	0.675	1.000	1.000	0.999	0.988
(34)	Std. Task 5	EA Score	0.331	1.000	1.000	0.980	0.928

This table presents p-values using different methods to correct for multiple hypothesis testing.