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2021-02

Series editors Dr Nicholas Rohde and Dr Athula Naranpanawa **ISSN** 1837-7750

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Cognitive and Non-Cognitive Traits and the Intergenerational Transmission of Socioeconomic Inequality*

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December 27, 2020

Abstract

This paper studies the roles of cognitive and non-cognitive skills in the intergenerational transmission of socioeconomic status. Using Australian microdata, we model the effects of individuals' backgrounds on adult income. Cognitive/non-cognitive skills are then examined as (i) additional direct determinants, (ii) path variables that transmit effects from other sources, and (iii) modifiers capturing heterogeneity across psychologically different individuals. We find that measurable psychological skills (intelligence, locus of control, big five personality traits) are slightly more important than background characteristics (such as race, gender, social class at birth) in explaining inequalities. Further, women and children from immigrant families develop higher levels of certain valuable skills, including conscientiousness and locus of control, which mask inequalities emerging from other sources. However in aggregate these effects are small, and background inequalities do not meaningfully reflect differences in cognitive or non-cognitive ability.

JEL Classification: D63, D91, J62

Key Words: Income Inequality, Inequality of Opportunity, Intergenerational Mobility, Personality

*The unit record data from the HILDA Survey were obtained from the Australian Data Archive, which is hosted by The Australian National University. The HILDA Survey was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views based on the data, however, are those of the author and should not be attributed to the Australian Government, DSS, the Melbourne Institute, the Australian Data Archive or The Australian National University and none of those entities bear any responsibility for the analysis or interpretation of the unit record data from the HILDA Survey provided by the author.

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1 Introduction

There are two opposing narratives that dominate public debate on the origins of economic inequality. One theory, popular on the political left, is that variations in socioeconomic outcomes mostly reflect societal failings, especially related to immutable factors such race, gender and social class at birth (Rank *et al.*, 2003). An alternative theory, popular on the right, is that inequalities often stem from differences in personal attributes, usually linked to diligence or merit (Lewis, 1998; Nozick, 1974). These differing explanations lie at the heart of many of the policy disagreements seen in developed economies. For instance, if poverty or relative deprivation are the result of persistent character flaws, then a broad social safety net may not be desirable, and policy should focus on correcting unhelpful personal behaviours. Conversely, if poor economic outcomes are exogenously determined, then a strong redistributive mechanism is needed, and policy makers should look to dismantle structural sources of disadvantage (Stiglitz, 2013; Atkinson, 2015; Andreoli *et al.*, 2019).

In this paper, we study economic inequality by examining the effects of uncontrollable factors, such as the socioeconomic and demographic characteristics of an individual's parents. Our goal is to shed light on the underlying transmission mechanisms - the how and why inequalities emerge from these background variables. In particular, we focus on the potential for individuals' cognitive (e.g. intelligence or ability) and non-cognitive (e.g. drive, persistence and personality) skills to play a role in this process. Since psychological skills are both valuable (Heckman *et al.*, 2006; Osborne-Groves, 2005) and partially inherited, either via genetics[1] or environmental factors experienced in early life (Panizzon *et al.*, 2014; Plomin and Deary, 2015), these factors have considerable potential for explaining how economic advantages are passed down over generations.

Our motivations are two-fold. Firstly, if cognitive or non-cognitive skills act causally to generate a meaningful share of economic inequality, and can be modified by policies that promote their development in utero or early childhood (e.g. Heckman and Kautz., 2013; Taylor *et al.*, 2017; Brinch and Galloway, 2012; Protzko *et al.*, 2013; Ritchie and Tucker-Drob, 2018), then harmful disparities can be partially mitigated with an appropriate set of interventions.[2] Thus, developing

[1] Monozygotic twin studies that focus on IQ scores typically assign between 50% and 85% of the variation in adult scores to parental intelligence. Similarly estimates of the heritibability in personality traits peak around 50%. For example Jang *et al.* (1996) estimate that genetics account for 41% of Emotional Stability, 53% of Extroversion, 61% of Openness, 41% of Agreeableness and 44% of Conscientiousness. Genetic heritability in locus of control is comparable to that of personality - see Miller and Rose (1982). The remainder is usually attributed to environmental factors (Benjamin *et al.*, 2012; Tellegen *et al.*, 1988). For these reasons, many researchers now consider psychological variables to constitute part of an individual's background (Lefranc et al., 2009; Ramos and Van der Gaer, 2013; Hufe et al., 2017), albeit one rarely examined within this context. Nonetheless, since individuals can exert some control over their mental state, disparities associated with psychological variables are sometimes regarded as relatively legitimate (Nozick, 1974), particularly for traits such as conscientiousness which may imply disutility from effort (e.g. see Jusot et al. (2013) for a discussion).

[2] For empirical evidence on the effects of policy see Mayer and Lopoo (2008). Other research shows that lowering background inequalities is likely to increase economic output (e.g. Marerro and Rodriguez, 2013; Brueckner and Lederman, 2018).

an understanding of which psychological traits matter, why they matter, and how they interact with other forms of inherited disadvantage can help guide this process.

We then look to address a common critique of the intergenerational inequality literature - that differentials associated with certain background characteristics might inadvertently reflect returns to unobserved cognitive/non-cognitive skills (Mankiw, 2013). Correlations of this form can create confounding problems, leading to estimates that either overstate (or potentially understate) the degree of socially determined disparity (Ramos and Van der Gaer, 2013; Ravallion, 2015). This confounding hypothesis is quite *prima facie* plausible, although the implications for inequality analysis depend in part on whether or not individuals are regarded as responsible for their own cognitive and non-cognitive skills.[3]

We examine these issues by exploring three major aspects of the transmission channel running from background characteristics to economic outcomes (these are illustrated in Figure 1 later in the paper). Firstly, we model the effects of cognitive and non-cognitive traits alongside traditional circumstances in the determination of economic wellbeing. Using regression models, we show that our psychological variables are slightly more important than race, gender and parental social class in generating inequalities. Of the explained component, our models attribute variations in living standards to psychological *vs.* these traditional circumstance variables in an approximately 60%-40% split. Thus, if we accept that individuals are not responsible for their endowments of cognitive/non-cognitive skills, psychologically disadvantaged individuals appear to represent a relatively important (and also under-emphasized) subgroup to target with redistributive policy.

The second mechanism we explore considers the direct heritability of psychological traits. Using econometric decompositions based on Jusot *et al.* (2013), Blanden *et al.* (2007) and Mahler and Ramos (2019), we model two-part transmission paths, where traditional background variables partially determine cognitive/non-cognitive skills, which then jointly affect income. Initially, we show that valuable traits such as conscientiousness and locus of control are partially determined by an individual's circumstances. For example, women, children from immigrant families, and children with high occupational-status fathers develop some of these skills at greater rates, which either heighten, or in certain cases mask, inequalities emerging from other sources.

However, we also show that the combined effect of this first stage is relatively small, with only 11-12% of our inequality estimates reflecting correlations between cognitive/non-cognitive skills and circumstance variables. Thus, estimates of predetermined inequality based on standard background characteristics are only slightly confounded by intelligence or character, which implies that

[3]In this paper we prefer the latter interpretation, as psychological skills are known to be primarily set by genetics, parental investment and childhood experience (Becker and Tomes, 1986; Borghans *et al.*, 2008; Reif *et al.*, 2007), and are usually solidified by adulthood (Costa and McCrae 1997; Cobb-Clark and Schurer, 2013).

some other causal channel(s) must be ultimately responsible. Factors correlated with an individual's background but omitted from the model (such as differing preferences or the presence of discrimination) are therefore likely to account for the majority of the income gaps associated with race, gender, and parental social class.

The third mechanism relates to interactions between traditional circumstance variables and our psychological indicators. In particular, we are interested in the potential for persons with high levels of cognitive/non-cognitive skills to overcome other forms of inherited disadvantage. Do highly skilled individuals reach a point where markers of inherited disadvantage no longer matter? Or are structural factors associated with background and ancestry always at play, such that even highly cognitively developed individuals are affected? If the former is true, this suggests that inherited inequalities can be lessened or perhaps even overcome, while the latter implies a high level of persistence in the effects of economic (dis)advantage. Using finite mixture models, we show that there are indeed meaningful interactions between these types of variables. For example, more intelligent and conscientious individuals seem to be less affected by their ancestral characteristics, and more influenced by their social class during childhood. However, a general finding like "the playing field is level for people with personality type X" does not emerge. Instead it appears that all individuals are, in aggregate terms, affected approximately equally by characteristics set at birth or during childhood. Therefore, while strong cognitive/non-cognitive skills are desirable in themselves, they offer only limited scope for mitigating the effects of other inherited disadvantages.

Our analysis embeds all three of these mechanisms within an *Inequality of Opportunity* (IOP) model, which allows us to reconcile our estimates with broader concepts of distributive justice (Roemer, 1998; Roemer and Trannoy, 2013). This conceptual framework defines *circumstances* as background factors that lie outside of personal control (such as the aforementioned race, gender and parental educational variables) and the inequalities produced represent differences in opportunity, corresponding to the structural or illegitimate forms (Bossert, 1995) outlined above. Conversely *efforts* reflect variations attributable to factors that lie within the bounds of personal responsibility. Since identifying circumstances is easier than identifying efforts, we focus our attention on the former.

The main contributions of are paper as follows. Our results present the strongest evidence (that we are aware of) that IOP estimates are not meaningfully confounded by cognition or personality. To our knowledge, we are also the first authors to show that strong psychological skills do little to lessen the effects of other sorts of inherited disadvantage - a belief which corresponds to a common refrain in some contemporary policy debates.[4] Alongside our estimates of the relative importance

[4] This is sometimes referred to as the "Horatio Alger Hypothesis" - the notion that individual merit can be enough to overcome inherited adversity. See Frank (2016) for a detailed discussion.

of circumstances *vs* psychological factors, our path decompositions are more extensive than those in related work (e.g. Anger and Heineck, 2009; Black and Devereux, 2010; Blanden *et al.*, 2007; Bowles and Gintis, 2002; Osborne-Groves, 2005). By breaking the intergenerational mechanism down into contributions from each specific circumstance (and flow-on effects via psychological factors) we obtain a highly detailed picture of how these factors interact to determine economic inequality.

The paper is structured as follows. Section 2 introduces our data set and provides detail on the specific variables used, while Section 3 outlines our modelling approach. Section 4 measures the direct effects of psychological traits on economic outcomes, and explores the potential for these variables to confound traditional measures of intergenerational inequality. Section 5 presents results on the heritability of cognitive and non-cognitive-skills, while Section 6 explores the idea that these psychological factors may exacerbate or even-out the effects of other circumstance variables. Section 7 concludes, while additional material related to the data and estimations is relegated to the appendix.

2 Data

Data come from the HILDA (Household Income and Labour Dynamics in Australia) panel, which is an approximately representative national survey similar in structure to the US PSID or German SOEP. The survey started in 2001 and has followed almost 20,000 individuals (about 7,000 households) with annual questionnaires on economic variables, demographics and family, origins, life events and other such factors. HILDA is especially useful as it simultaneously contains both highly detailed data on background characteristics, and extensive information on individuals' psychological make-up. Indeed the richness of the psychological variables available is a key feature of our data.

We draw observations from three clusters of variables, related to (i) adult household income (as a measure of living standards), (ii) traditional indicators of an individual's inherited circumstances, and (iii) psychological factors that are usually omitted from IOP studies, but may also affect economic outcomes. The psychometric data include several measures of intelligence (representing cognitive skill), various markers of personality, and indicators of self-determination (capturing non-cognitive skill). A brief outline of each set of variables is given below.

Income

Economic wellbeing is measured using real household equivalent income, which is the sum of all inflows to all members, minus outflows including taxes and transfers. As we will use log transforms zero incomes are dropped, although due to the inclusion of transfer payments these comprise only 0.35% of the sample. We employ the Buhmann *et al.* (1988) $\psi = 0.5$ correction to account for economies of scale within households, and to prevent outliers from disproportionately driving our results, we trim our sample by excluding the most extreme 1% (i.e. the top and bottom 0.5%) of annual observations.[5] Data are taken from 14 years, since the first wave capturing all our key covariates in 2002.

As is standard in this literature, we also conduct a pre-analysis adjustment to account for life-cycle factors, such that covariates related to age and time can be omitted from subsequent regressions. Accounting for age is important as older individuals normally have higher incomes, and year-specific effects need to be controlled for as attrition results in fewer observations towards the end of the period (where incomes are typically higher). To correct for these factors, we estimate the model $\ln(y_{it}) = \mathbf{x}_t'\boldsymbol{\delta} + f(age_i) + \varepsilon_{it}$ where $\mathbf{x}_t'$ is a vector of annual dummies, $\boldsymbol{\delta}$ a vector of parameters, and $f(age)$ a {0-4} fractional polynomial function capturing changes over the life-cycle. We then employ the corrected variable $\ln(y_{it})^* = \mathbf{x}_t'\boldsymbol{\delta} + \overline{\ln(y)} + \varepsilon_{it}$ as a measure of annual income. Since annual incomes can be volatile, we also produce $Q = 5$ year longitudinal averages using $\ln(y_{it})^{**} = Q^{-1}\sum_{p=t-Q+1}^{t} \mathbf{x}_t'\boldsymbol{\delta} + \overline{\ln(y)} + \varepsilon_{ip}$ as a secondary "permanent" variable that smooths away transitory variations (see Aarberge *et al.*, 2011).[6] Due to the presence of missing values, the permanent measure (which requires observations in all periods) has a slightly reduced sample size.

Background Characteristics

Data on background characteristics are chosen in order to capture the environment that an individual inherits, either at birth, or in early childhood. The idea here is to measure as broadly as possible the types of circumstances that could determine economic outcomes. We infer an individual's background using a number of proxy measures of ancestry, including dummies for

[5]Our econometric models make distributional assumptions that are sometimes sensitive to outliers, and hence by eliminating extreme values we are able to obtain better goodness-of-fit statistics. As a consequence our results are not likely to be applicable for observations in the extremities of the income distribution.

[6]As our income variables require some small statistical adjustments, this process may generate measurement error, which would add an additional source of variation to our models. However as only the dependent variable is affected any error will not bias our estimates. These corrections also imply that the standard errors reported in our models will be slightly understated due to the consumption of degrees of freedom in the adjustment process. However as our sample sizes are large ($n > 9000$ in all cases) these effects will be negligible.

(i) migrancy, (ii) paternal and maternal immigration status, (iii) refugee status, (iv) racial background (being of Aboriginal or Torres Strait Islander decent), and (v) whether or not an individual speaks English as their native language. Disparities associated with gender are also captured with a dummy. Parental social class is then measured with the educational attainments of both the mother and father (primary education; up to Year 10 education; beyond Year 10 education). However as these variables are not particularly granular, we also employ continuous markers of socioeconomic/occupational prestige for both parents. Developed by sociologists McMillan *et al.* (2009), these indices are generated from various underlying factors including education, income and job type, forming 0-100 scales where higher numbers indicate greater status.[7] Lastly, as economic experiences during childhood are likely to be important (Guo, 2018), we use indicators of whether or not the mother was engaged in full time employment, if the family is broken up at age 14, and another if the father experienced a spell of unemployment by that age.[8]

Cognitive/Non-Cognitive Markers

We draw psychometric data on three primary constructs (intelligence, personality, locus of control).[9] Traits such as these may also determine economic wellbeing, acting through a variety of behavioral channels. For instance, cognition, motivation, discipline, and self-determination will influence a host of economic decisions, including educational choices, health management, labor supply and marriage or cohabitation (e.g. Heckman, 2007). Details on each variable type are given below, and additional descriptive information related to their covariance structure is presented in the appendix. These variables change during childhood and in old age, but are generally are stable over adulthood (Cobb-Clark and Schurer, 2013). To be able to treat these as time invariant we restrict our sample to individuals aged 20-65. This intertemporal stability also allows us to impute missing values based upon an individual's score in an earlier or latter period. In our case, as we have multiple observations on these variables, we take longitudinal averages and hence eliminate any time variation within our data set. While this prevents any dynamics in cognition from informing our estimations, it has the desirable effect of reducing measurement error (Viswesvaran and Ones, 2000; Whitaker, 2010).[10]

[7]These scales are based upon income, age, education, hours worked, occupation and various other socioeconomic factors. As such they are only directly measured for parents that are employed, but are imputed based upon educational qualifications for persons outside of the labor force.

[8]We are therefore setting the *Age of Responsibility* for efforts as greater than 14. See Brunori *et al.* (2013).

[9]As these types of variable are costly to administer, they are only recorded intermittently in our data. The intelligence tests we use appear in the 2012 wave while the personality traits and locus of control questions appear in waves 2009 and 2013; and 2007, 2011 and 2015 respectively.

[10]Nonetheless there is little intertemporal variation in our data. Bowles and Gintis (2012) also argue that measurement error in psychometric data is reasonably small.

Intelligence

Cognition is widely established as a primary determinant of human capital development, and returns to intelligence tend to be particularly high in developed countries like Australia (Murnane *et al.*, 1995). We employ two specifically designed indicators - the Backwards Digit Span (BDS), and scores from the Symbol Digit Modalities test (SDM). Both have been extensively validated, and commonly employed in empirical work (Wooden, 2013).[11] The BDS measures short-term memory (which is correlated with other markers of intelligence) by asking subjects to recall in reverse order a series of digits read to them by an examiner. Participants are allowed two attempts at each, and when they are successful they are presented with a longer series, up to a maximum of eight digits. The score is determined by the dimension of the longest series recalled. Our other metric (the SDM) searches for signs of cognitive impairment by giving subjects 90 seconds to match unfamiliar symbols with digits using a key-code assigned by an examiner. The score on the SDM is the number of correct matches, where higher numbers indicate greater cognitive ability.

Big Five Personality Traits

As with cognition, personality may affect behavior, forming an additional intermediary between circumstances and outcomes. We measure personality using the "big five traits" which describe commonly observed variations in character (John and Srivastava, 1999; Costa and McCrae, 1985). These taxonomies represent one of the core tools for analyses in social psychology, and are obtained via factor analyses of Likert-type survey responses to descriptive statements such as *"Easy to talk to*"; *"Worries a lot"*; *"Has a forgiving nature"*; or *"Remains calm in tense situations".* Some associated adjectives for high/low predispositions of each dimension are given below.

Openness to Experience: - Curiosity / experimentation *vs.* consistent / cautious.

Conscientiousness: - Disciplined / organized *vs.* carefree / disorganized.

Extroversion: - Outgoing / energetic *vs.* self-sufficiency / reserved.

Agreeableness: - Compassionate / submissive *vs.* antagonistic/ assertive.

Emotional Stability: - Sensitivity / anxiety *vs.* calmness / indifference.

[11] A third indicator obtained from the National Adult Reading Test (NART) is also available. The NART examines subject vocabulary using 50 unusually spelled English words and is designed to be a measure of pre-morbid intelligence. The test functions by exploiting the high correlation between reading ability and cognitive skill, however as it is not appropriate for non-native English speakers (a subgroup we are especially interested in) and hence it is not employed here. Nonetheless, the fact that this measure is also correlated strongly with the other two measures reinforces the claim that intelligence is adequately captured and not especially influenced by the medium (i.e. numerical/symbolic/language) chosen.

Again, it is intuitive to see that these might either (i) directly affect living standards, or (ii) produce heterogeneity in the ways that individuals approach economic challenges. For example, conscientiousness relates to an individual's work ethic, and has been shown to predict a wide variety of economic outcomes (Borghans *et al.*, 2008). Similarly, extroversion may assist with interpersonal communication, while openness to experience suggests inventiveness and risk tolerance. These factors are likely to be beneficial for individuals working in creative or scientific fields, but may also predict risky behaviors such as gambling (Gong and Zhu, 2019), dangerous driving, or drug abuse (Gullone and Moore, 2000). Emotional stability also predicts job performance in certain careers (Barrick and Mount, 1991), and affects lifestyle variables (which in turn affect economic outcomes) such as relationship decisions (Shaver and Brennan, 1992). Lastly, agreeableness fosters beneficial co-operation, but in high levels, can imply a lack of assertiveness (McCord *et al.*, 2014).

Locus of Control

Our second cluster of non-cognitive variables relates to an individual's locus of control. This construct is intended to capture the degree to which an individual believes they are able to exert influence over their own lives (Lefcourt, 1976). A person who feels they are able to influence their own life is said to have an internal locus of control, while a person with an external locus feels they are mostly affected by outside factors. Again this trait can be conceptually linked to the ways in which individuals tackle disadvantages. For example, individuals with a greater sense of self determination might be more adept at navigating adverse economic terrain, or respond better to negative shocks or challenging life events (Buddelmeyer and Powdthavee, 2016).

Our measures of an individual's locus of control are obtained from four subjective 1-7 scales designed to capture an individual's sense of self-determination.[12] These questions ask for agreement/disagreement with the statements (I) *"Can do just about anything"*, *"Cannot change important things in life"*, feel *"Pushed around"* and see *"No way to solve problems"*. When the implicit orderings of the questions are reversed, we invert the scales such that higher values always indicate a *weaker*, or *more external*, locus of control.

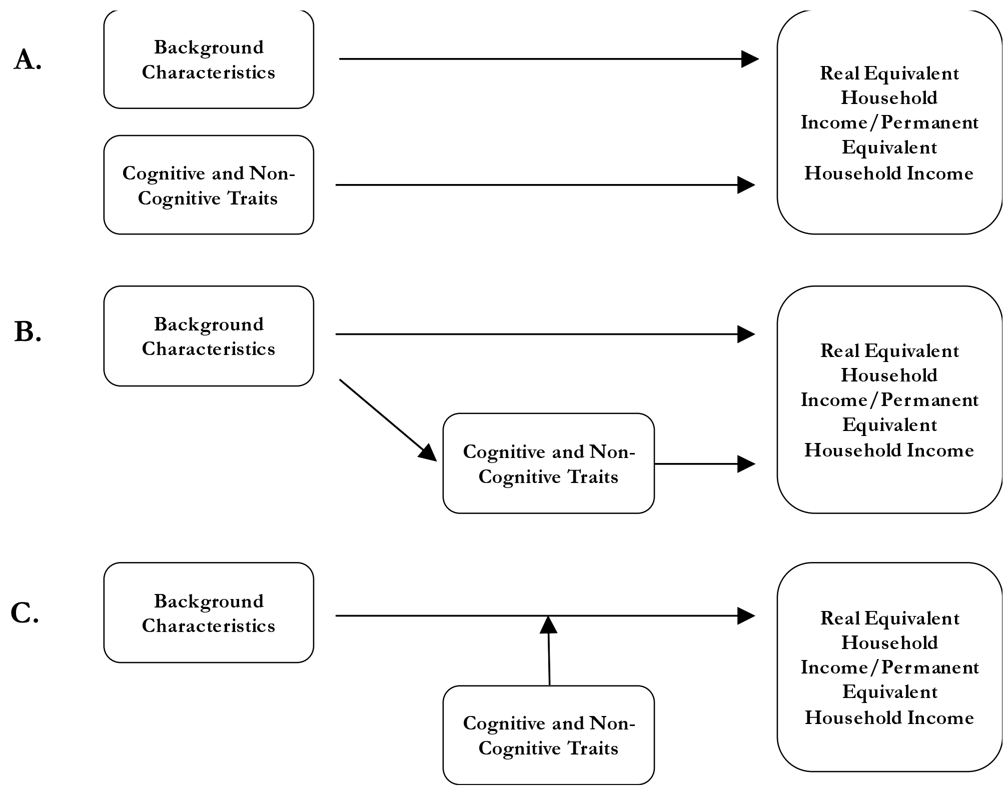
3 Econometric Approach

We now consider three possible mechanisms through which cognitive and non-cognitive skills can

[12] There are actually seven of these variables in our data set however the correlations between these variables are strong enough to interfere with identification of the model presented in Section 5. This problem can be circumvented by excluding some regressors. As we wish to retain consistency across models we drop these variables from the outset, but note that the results are not sensitive to which are included.

interact with background characteristics to affect outcomes.[13] These mechanisms are outlined in Figure 1 below, and are addressed sequentially in the paper. In all cases we will make the standard assumption of exogeneity for the background variables, which is plausible since they are predetermined with respect to adult income. Similarly, we will treat background characteristics as drivers of our psychological variables, which may in turn go on to affect income. Thus we can rule-out endogeneity problems associated with reverse-causal flows, although other potential sources of bias (through omitted variables, or measurement error on the independent variables) remain.

Figure 1: Flow Diagram Illustrating Direct, Indirect and Moderating Effects



Note: The Figure illustrates the three major causal channels studied in the paper. Subset A shows independent direct effects of background characteristics and psychological traits on incomes. Subset B illustrates a mediating effect whereby background characteristics impact upon outcomes directly and via their effects on psychological traits. Subset C shows a moderation effect where only background characteristics impact directly upon incomes but the effect sizes are altered by psychological traits.

Addressing mechanisms A-C requires an econometric approach that ties two separate forms of regression-based decomposition with additive decomposition as developed in the inequality litera-

[13]Other mechanisms such as segregation (which has the capacity to generate inequality in the absence of group differences) are not explored. See Bowles *et al.* (2014).

ture. The former set of properties allow us to exhaustively decompose variations in outcomes into contributions from covariates, while the latter allows us these estimates to be reconciled with an axiomatically derived metric for measuring IOP.

While we are unaware of any approach that can merge these forms of decomposition, we show that an approximate method (based upon an equivalency between the Variance of Logarithms and Generalized Entropy (GE) measures) that serves this purpose can be built by assuming lognormality of the dependent variable. Below we (i) outline our inequality measure, (ii) combine the explained component with a regression-based decomposition, and (iii) show that in this special parametric case, the inequality attributed to circumstances can be further decomposed into contributions from each variable. Since these covariate-specific contributions are obtained from transformed marginal effects, this allows us to correct for confounding in IOP estimates.

Decomposable Inequality Metrics

We begin by specifying the inequality metric. Assessing relative contributions to inequality requires a measure that satisfies the following axioms: (i) *Anonymity*, (ii) *Symmetry*, (iii) *Pigou-Dalton Transfer Sensitivity*, (iv) *Mean Invariance*, (v) *Replication Invariance* and (vi) *Additive Decomposition.* Shorrocks (1980) shows that these uniquely identify the parametric class of GE measures:

$$I_\theta(y) = \frac{1}{\theta^2 - \theta}\left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i}{\bar{y}}\right)^\theta - 1\right], \qquad \theta \neq 0,\, 1 \tag{1}$$

Here $I_\theta(y) \in R^1_+$ is the inequality metric, $y \in R^n_{++}$ an income distribution, y_i the income of individual i, $\bar{y}$ the average, and θ a sensitivity parameter. Special cases of EQ (1) include Theil's L measure ($\theta \to 0$), T measure, ($\theta \to 1$), and half the squared Coefficient of Variation ($\theta = 2$). Additional axioms useful for measuring IOP include (vii) *Path Independence* (Foster and Shneyerov, 2000),[14] (viii) *Arithmetic Mean Reference* and (ix) *Population Share Weights*, which restrict EQ (1) to Theil's L (or $I_{\theta\to 0}(y)$ - also known as the Mean Log Deviation) as a member of this class (Checchi and Peragine, 2010; Ferreira and Gignoux, 2011).

A non-parametric decomposition of EQ (1) is as follows. If sample $i = 1, ..., n$ is divided into $j = 1, ..., k$ subgroups (where $n >> k$) of size n_j with means $\bar{y}_j = \frac{1}{n_j}\sum_{i\in j} y_{ij}$, $I_{\theta\to 0}(y)$ can be written as:

[14] Path Independence implies within/between decompositions provide the same result regardless of which is performed first. Roemer and Trannoy (2013) point out that two conceptualizations of IOP the *fairness gap*, and *direct unfairness* coincide only for this index. The former calculates inequality of outcomes due to efforts within subgroups that control for circumstances. The latter is the inequality explained across circumstance groupings using the ratio of individual incomes to subgroup incomes.

$$I_{\theta\to 0}\left(y;\bar{y}_1...\bar{y}_k;n_1...n_k\right)=\frac{1}{n}\sum_{i=n}^{n}-\ln\left(\frac{y_i}{\bar{y}}\right)=\sum_{j=1}^{k}\frac{n_j}{n}I_j\left(y_{ij};\bar{y}_j\right)+\sum_{j=1}^{k}-\ln\left(\frac{\bar{y}_j}{\bar{y}}\right) \tag{2}$$

or $I_{\theta\to 0}\left(y\right) = I_U\left(y\right)+I_E\left(y\right)$, where $I_E\left(y\right)=\sum_{j=1}^{k}-\ln\left(\bar{y}_j/\bar{y}\right)$ is the inequality explained by group membership $j=1,...,k$, $I_U\left(y\right)=\sum_{j=1}^{k}\left(n_j/n\right)I_j\left(y_{ij};\bar{y}_j\right)$ the aggregate inequality within the groups, and $I_j\left(y_{ij};\bar{y}_j\right)=\sum_{i\in n_j}-\ln\left(y_{ij}/\bar{y}_j\right)$ the inequality internal to j.[15] If the subgroups reflect circumstances (e.g. gender or racial groupings) then $I_E\left(y\right)$ is an absolute measure of IOP, while $I_R\left(y\right)=I_E\left(y\right)/\left(I_E\left(y\right)+I_U\left(y\right)\right)$ gives the relative inequality explained by these groups. It is this ratio that is usually the primary estimate of interest.

Regression-Based Decomposition

The non-parametric subgroup decomposition above can be generalized with regression models. Replace the k subgroups above with $x_1,...,x_k$ measuring background characteristics. The regression $y=\beta_0+\sum_{j=1}^{k}\beta_k x_k+\varepsilon$ plays the same role as the subgroup partitioning, where the fitted value $\hat{y}_i$ replaces $\bar{y}_j$ in EQ (2), and the summation is performed over i rather than j.[16] That is,

$$I\left(y;x\right)=\frac{1}{n}\sum_{i=1}^{n}-\ln\left(\frac{y_i}{\hat{y}_i}\right)+\frac{1}{n}\sum_{i=1}^{n}-\ln\left(\frac{\hat{y}_i}{\bar{y}}\right)=I_U\left(y;x\right)+I_E\left(y;x\right) \tag{3}$$

where $I_U\left(y;x\right)$ and $I_E\left(y;x\right)$ are interpreted as above. This model takes on some convenient properties when $y\sim\ln\mathcal{N}\left(\mu,\sigma^2\right)$.[17] We assume a model for the unconditional density of y

$$f\left(y;\mu,\sigma^2\right)=\frac{1}{y\sqrt{2\pi\sigma^2}}\exp\left[-\frac{\left(\ln y-\mu\right)^2}{2\sigma^2}\right]\qquad y>0,\ \sigma>0,\ \mu\in\left(-\infty,\infty\right) \tag{4}$$

such that any scale invariant measure (Axiom iv - i.e. independent of μ) will depend only on σ^2. For example, denote the CDF for the standard normal $\Phi\left(y\right)=P\left(Y<y\right)$. The Gini coefficient is obtained $G\left(y\right)=2\Phi\left(\sigma/\sqrt{2}\right)-1$, while the Pietra index is $P\left(y\right)=2\Phi\left(\sigma^2/2\right)-1$ and the Coefficient of Variation is $CV\left(y\right)=\sqrt{\exp\left(\sigma^2\right)-1}$. Parameter σ^2 itself is a common *ad hoc*

[15] IOP estimates of this form are known as *ex ante* inequalities. Estimates that homogenize on efforts and measure disparities due to circumstances are *ex pos*t measures (Fleurbaey and Peragine, 2013).

[16] As EQ (2) is only defined for $y>0$ and $\bar{y}>0$, some transformation such as logarithmic or inverse hyperbolic sine on the dependent variable is common.

[17] Lognormals have been widely used to model the size distribution of income (e.g. Pinkovskiy and Sala-i-Martin, 2009) due to their non-negative support and heavy right tail. In Appendix A3 we show this approximation holds closely in our data.

measure known as the Variance of Logarithms, which fails to satisfy Axiom (iii) (Foster and Ok, 1999). However under our distributional assumptions this violation is precluded, and the index is also proportional to $I_{\theta\to 0}(y)$ in EQ (3). To illustrate for $I(y)$, consider that in EQ (3) is an estimate of $\ln(E(y)) - E(\ln(y))$, where for a lognormal, $E(y) = \exp\left(\mu + \frac{1}{2}\sigma^2\right)$ and $E(\ln(y)) = \mu$. Via Jensen's inequality the former term is always larger, in this case by the constant $\frac{1}{2}\sigma^2$. Further, if $\hat{y} \sim \ln\mathcal{N}(\mu, \sigma_E^2)$ then the inequality ratio $I_R(y;x) \approx \sigma_E^2 / (\sigma_U^2 + \sigma_E^2)$ is equal to the R^2 term from a regression where the LHS variable is $\ln(y)$. This requires the conditional variance ($Var(\varepsilon | x_1, ..., x_k) = \sigma_U^2$) to be constant (i.e. a homoskedasticity assumption), as inequality is being measured using scalar summaries across the full sample.[18]

Covariate-Specific Decomposition of $I_R(y;x)$

Estimating $I_R(y;x)$ as the explained component from a regression is desirable, as this can be merged with an additional decomposition, advanced by Bowles and Gintis (2002), Fields (2003), Mordoch and Sicular (2002) and Fiorio and Jenkins (2010). If appropriately transformed, the R^2 term from a regression can be written as a linear sum of the regression parameters.[19] If $x_1, ..., x_k$ continue to denote background variables, and $z_1, ..., z_k$ psychological variables, define the transformed terms $\ln(\tilde{y}_{it}) = (\ln(y_{it}) - \ln(\bar{y}_{it}))/\sigma_{\ln y}$, $\tilde{x}_{ijt} = (x_{ijt} - \bar{x}_j)/\sigma_{z_j}$ and $\tilde{z}_{ijt} = (z_{ijt} - \bar{z}_j)/\sigma_{z_j}$. This normalizes $\sigma^2_{\ln \tilde{y}} = 1$ such that the overall inequality estimate is obscured, however we can reconstruct this value by rescaling by our estimates by $\sigma^2_{\ln y}$. The equation is:

$$\ln(\tilde{y}_{it}) = \alpha + \sum_{j=1}^{k} \beta_j \tilde{x}_{jit} + \sum_{l=1}^{m} \phi_l \tilde{z}_{lit} + \varepsilon_{it}, \quad \varepsilon_{it} \sim \mathcal{N}\left(0, \sigma^2\right) \tag{5}$$

This becomes a Random Effects model with the additional error structure $\varepsilon_{it} = \alpha_i + u_{it}$ and assumption $\mathrm{cov}(\alpha_i; \tilde{x}_{jit}, \tilde{z}_{lit}) = 0$. Nonetheless we employ the pooled ML estimator of the RE model (which is consistent although inefficient when $\alpha_i \neq \alpha$) but is advantaged as (i) it allows for a direct calculation an overall R^2 term, and (ii) the literature on IOP offers little guidance in how to interpret α_i, which reflects time-invariant individual-specific factors unrelated to background characteristics. The decomposition we employ is based on R^2 being equal to a linear sum of each regression coefficient, multiplied by the correlation of the corresponding variable with $\ln(y)$. Using the equivalency with $I_R(y;x)$, we can write out component captured by the regressors as a sum over j and l of parameter estimates from EQ (5):

[18] Nonetheless robust covariance can be used for inference.

[19] Note that a random effects specification is required here as our background covariates are time invariant.

$$I_R(\beta,\phi,\rho)=\sum_{j=1}^{k}\beta_j\rho\left(\ln\left(y\right);x_j\right)+\sum_{l=1}^{m}\phi_l\rho\left(\ln\left(y\right);z_l\right) \tag{6}$$

$$I_E\left(\beta,\phi,\rho,\sigma^2\right)=\sum_{j=1}^{k}\sigma^2_{\ln y}\beta_j\rho\left(\ln\left(y\right);x_j\right)+\sum_{l=1}^{m}\sigma^2_{\ln y}\phi_l\rho\left(\ln\left(y\right);z_l\right) \tag{7}$$

The intuition behind EQ (5) and EQ (6) allows us to individually unpack the contributions of each variable. For example, if covariate x_j predicts a higher income then we expect $\beta_j > 0$. If this attribute is also concentrated in the high end of the income distribution, then $\rho\left(\ln\left(y\right);x_j\right) > 0$ and the combined effect (given by the product of these terms) will be positive. As such, x_j stretches out the right tail of the income distribution and therefore acts to increase inequality. Equally, if a particular covariate increases incomes but is concentrated amongst poorer individuals (e.g. a dummy denoting eligibility for income support), then the product of β_j and $\rho\left(\ln\left(y\right);x_j\right)$ would be negative, capturing the inequality-reducing effect from compressing the left tail of the distribution of outcomes.

The regression model in EQ (5) also links intuitively to IOP. This model separates each individual's income into (i) a "smoothed" value (given by $\alpha+\sum_{j=1}^{k}\beta_j x_{jit}+\sum_{l=1}^{m}\phi_{lit}z_{lit}$), which captures the degree to which the value is predetermined, and (ii) a residual component ε_{it}, which captures all other factors uncorrelated with x. The idea is that as ε_{it} will contain a heterogeneous collection of factors (measurement error, individual effort, luck, genetics, other unobserved circumstances), it is desirable not to interpret this term as either a legitimate or an illegitimate inequality. However as the explained term is completely exogenous, this provides an uncontaminated estimate of the inequality generated by x and z.[20]

4 Inequality of Opportunity with Psychological Traits

The first channel (Mechanism A) explores the idea that psychological factors could account for a meaningful share of the disparities in outcomes. The primary goals here are to obtain baseline IOP estimates and to determine which background factors account for the most variation. We then re-estimate the regressions including cognitive and non-cognitive variables alongside the traditional background markers, such that we can establish similar results for the psychological variables, and calculate the relative contributions of backgrounds versus cognitive/non-cognitive skills. When

[20]Since we do not observe an individual's full set of circumstances, this estimate is interpreted as a lower bound on the true level of IOP.

estimating models where some covariates are measured post-treatment (as in the psychological variables are established after background characteristics) we require the additional assumption that $Cov(\varepsilon_1, \varepsilon_2) = 0$, where ε_1 is the error from EQ (4) and ε_2 the error from a regression of z on x (Angrist and Pischke, 2009; Hayes and Rockwood, 2017).

Table 1 below presents estimates of EQ (4) where we only include standard background characteristics. Table 2 then presents estimates from the full models with both sets of covariates included. In each case we report the normalized coefficient $\hat{\beta}_j$, the correlation of variable j with $\ln(y_{it})^{*}$ or $\ln(y_{it})^{**}$, $(\hat{\rho}(\ln(y); x_j))$, and the product terms $\hat{\beta}_j \hat{\rho}(\ln(y); x_j)$. The key estimates are those presented in the last rows, which give $I_R(x, z; \beta, \phi)$ and $I_E(x, z; \beta, \phi, \sigma^2)$.

Table 1: Estimates of Inequalities of Opportunity: - Standard Background Characteristics

		Annual Income $\ln(y_{it})^{*}$			Permanent Income $\ln(y_{it})^{**}$		
Variable		$\hat{\beta}_j$	$\hat{\rho}_{yj}$	$\hat{\beta}_j\hat{\rho}_{yj}$	$\hat{\beta}_j$	$\hat{\rho}_{yj}$	$\hat{\beta}_j\hat{\rho}_{yj}$
Background	Female	-0.0181	-0.0170*	0.0003	-0.0240	-0.0234**	0.0006
	Born Non-English Country	-0.1147***	-0.0342***	0.0039	-0.1302***	-0.0436***	0.0057
	Non-Native English Speaker	0.0252	-0.0216**	-0.0005	0.0179	-0.0308***	-0.0006
	Arrived as Refugee	-0.0139	-0.0344***	0.0005	-0.0160	-0.0401***	0.0006
	Father Migrated to Aust	0.0454	0.0204**	0.0009	0.0652**	0.0287***	0.0019
	Mother Migrated to Aust	-0.0135	0.0059	-0.0001	-0.0207	0.0071	-0.0001
	Aboriginal or Torres Strait Is.	-0.0398*	-0.0541***	0.0022	-0.0541**	-0.0698***	0.0038
	Father Ed Primary	-0.0089	-0.0547***	0.0005	-0.0001	-0.0558***	0.0000
	Mother Ed Primary	0.0368	-0.0389	-0.0014	0.0332	-0.0445***	-0.0015
	Father Ed 10 Plus	0.0607**	0.1356***	0.0082	0.0771***	0.1535***	0.0118
	Mother Ed 10 Plus	0.0440*	0.1235***	0.0054	0.0361	0.1317***	0.0047
	Father Occupational Status	0.0987***	0.1622***	0.0160	0.1083***	0.1804***	0.0195
	Mother Occupational Status	0.0668***	0.1304***	0.0087	0.0805***	0.1477***	0.0119
	Father Unemployed at Age 14	-0.0598***	-0.0710***	0.0042	-0.0623***	-0.0767***	0.0048
	Mother Works at Age 14	0.0317	0.0358***	0.0011	0.0368	0.0415***	0.0015
	Parents Broken Up at Age 14	-0.0216	-0.0218**	0.0005	-0.0381*	-0.0376***	0.0014
Misc	Constant	3.15E-10			-0.0003		
	n	9,411			9,377		
	R^2	0.0504			0.0662		
	$\hat{\sigma}^2_{\ln y}$	0.2384			0.2013		
	$\ln(\mathcal{L})$	-13110			-12984		
Inequality	$I_E(x, z; \beta, \phi)$			0.0504			0.0662
	$I_E\left(x, z; \beta, \phi, \sigma^2\right)$			0.0479			0.0619

Note: The table presents estimates from EQ (1) excluding covariates capturing cognitive/non-cognitive traits. Parameters are estimated by Maximum Likelihood with cluster robust covariance. Results for annual incomes are presented on the left while estimates for permanent income are given on the right. In each case the leftmost columns give standardized regression coefficients (i.e. where all variables are z transformed) while the second columns show correlations between each variable and the dependent variable. The product of the terms is then given in the rightmost columns. Aggregating these terms gives the proportion of total inequality explained - $I_R(x, z; \beta, \phi)$ - which is interpreted as the fraction of inequality attributed to the circumstances. Multiplying this term by the variance gives the absolute inequality of opportunity metric $I_E\left(x, z; \beta, \phi, \sigma^2\right)$.

By examining the estimates and correlations in Table 1, we can measure IOP in our data and identify the factors that have the biggest role in explaining inequality. For annual incomes, the relative explained inequality $I_r(x, z; \beta, \phi)$ is 0.0504 (and an absolute estimate for $I_A(x, z; \beta, \phi, \sigma^2)$ of 0.0120), indicating that 5.04% of the total inequality can be explained by looking at our circumstance variables alone. Notably this estimate of the relative share is fairly low (i.e. we are attributing almost 95% of the inequality to efforts, unobserved circumstances, and data/modeling issues such as measurement and specification error). However, there are a few reasons to expect an estimate of around this size. Affluence tends to predict lower rates of intergenerational transmission (Aydemir and Yazici, 2019), and parametric estimates for high income European countries tend to range between 0-10% (Brunori *et al.*, 2013; Checchi *et al.*, 2015), Further, intergenerational earnings elasticities (an alternative IOP measure) in Australia are substantially lower than in other developed nations (Corak, 2013; Leigh, 2007).

Turning to the estimates in the first column, we see that the variables with the largest magnitudes (i.e. the estimates of β_j that differ most from zero in column 1) are (i) being born in a non-English speaking country, (ii) having a father who experienced a spell of unemployment during childhood (negative signs), (iii) coming from parents with greater that year 10 education, and (iv) having parents with high occupational status (positive signs). The parental social class variables are also positively correlated with income, while the correlations for being born in a non-English country and paternal unemployment are negative.

Taking the product terms, we see that the variables that account for the most inequality of opportunity are the two sociological measures of parental occupational status, and the indicators for having at least a Year 10 education (for both parents). These four variables alone make up almost 75% of the total inequality of opportunity estimate. This suggests that factors related to social class at birth are much more important than either gender or ancestral variables (with being born outside of Australia being an exception) or socioeconomic events experienced by the family while young.

The results for five-year incomes in the rightmost three columns tell a similar story. In this case, the dependent variable is less volatile and hence a greater proportional degree of inequality can be captured by our covariates (i.e. $I_R(x, z; \beta, \phi)$ is 6.62% as opposed to 5.04%), although the total inequality is similar $\{0.0120$ *vs.* $0.0133\}$. Again the variables with the highest standardized regression coefficients relate to country of birth and parental education/occupation, and the correlations with the dependent variable run the same way as for annual income. In this instance, the paternal occupational status variable in isolation accounts for almost 30% of the explained inequality, while the maternal variable is almost 20%. Aggregating across the parental educational and occupational status variables again gives an explained component of approximately 75%, reinforcing the notion that our parental socioeconomic status indicators are more effective at accounting for inherited inequality than the ancestral or early life experience variables.

Estimation Including Psychological Traits

The models depicted in Table 2 simultaneously consider the effects of background variables and cognitive/non-cognitive traits. Our first objective is to work out how important cognitive and non-cognitive skills are relative to standard background characteristics, while in Section 4 we will use the same models to determine whether the correlations presented in Table 1 might be driven by factors related to intelligence or character that are typically omitted from IOP models.

Table 2: Ex Ante Inequalities of Opportunity: - Background Characteristics and Cognitive/Non-Cognitive Skills

		Annual Income $\ln(y_{it}^{*})$			Permanent Income $\ln(y_{it}^{**})$		
Variable		$\hat{\beta}_j/\hat{\phi}_l$	$\hat{\rho}_{yj}$	$\hat{\beta}_j\hat{\rho}_{yj}$	$\hat{\beta}_j/\hat{\phi}_l$	$\hat{\rho}_{yj}$	$\hat{\beta}_j\hat{\rho}_{yj}$
Background	Female	-0.0541**	-0.0170*	0.0009	-0.0639***	-0.0234**	0.0015
	Born Non-English Country	-0.0839*	-0.0342***	0.0029	-0.0993**	-0.0436***	0.0043
	Non-Native English Speaker	0.0095	-0.0216**	-0.0002	0.0026	-0.0308***	-0.0001
	Arrived as Refugee	-0.0150	-0.0344***	0.0005	-0.0172	-0.0401***	0.0007
	Father Migrated to Aust	0.0316	0.0204**	0.0006	0.0504	0.0287***	0.0014
	Mother Migrated to Aust	-0.0164	0.0059	-0.0001	-0.0234	0.0071	-0.0002
	Aboriginal or Torres Strait Is.	-0.0336	-0.0541***	0.0018	-0.0473*	-0.0698***	0.0033
	Father Ed Primary	0.0132	-0.0547***	-0.0007	0.0240	-0.0558***	-0.0013
	Mother Ed Primary	0.0347	-0.0389***	-0.0014	0.0321	-0.0445***	-0.0014
	Father Ed 10 Plus	0.0575**	0.1356***	0.0078	0.0744***	0.1535***	0.0114
	Mother Ed 10 Plus	0.0284	0.1235***	0.0035	0.0182	0.1317***	0.0024
	Father Occupational Status	0.0925***	0.1622***	0.0150	0.1016***	0.1804***	0.0183
	Mother Occupational Status	0.0627***	0.1304***	0.0082	0.0768***	0.1477***	0.0113
	Father Unemployed at Age 14	-0.0581***	-0.0710***	0.0041	-0.0613***	-0.0767***	0.0047
	Mother Works at Age 14	0.0162	0.0358***	0.0006	0.0189	0.0415***	0.0008
	Parents Broken Up at Age 14	-0.0270	-0.0218**	0.0006	-0.0442**	-0.0376***	0.0017
Cognitive	Backward Digit Span	0.0007	0.0643***	0.0000	0.0164	0.0853***	0.0014
	Symbol Digit Modalities	0.1027***	0.1505***	0.0155	0.1112***	0.1676***	0.0186
Personality	Agreeableness	0.0327	0.0285***	0.0009	0.0364	0.0275***	0.0010
	Conscientiousness	0.0979***	0.1257***	0.0123	0.1118***	0.1354***	0.0151
	Emotional Stability	-0.0500**	0.0312***	-0.0016	-0.0614**	0.0275***	-0.0017
	Extraversion	-0.0160	0.0236**	-0.0004	-0.0206	0.0192*	-0.0004
	Openness to Experience	-0.0478	-0.0056	0.0003	-0.0647***	-0.0118	0.0008
Loc of Con	Can Do Anything - R	-0.0103	-0.0929***	0.0010	-0.0124	-0.0982***	0.0012
	Cannot Change Things	-0.0426	-0.1727***	0.0074	-0.0515	-0.1854***	0.0095
	Feel Pushed Around	-0.0276	-0.1486***	0.0041	-0.0100	-0.1489***	0.0015
	No Way To Solve Problems	-0.0734**	-0.1656***	0.0122	-0.0842**	-0.1774***	0.0149
Misc	Constant	-3.16E-10			-0.0007		
	n	9,411			9,377		
	R^2	0.0958			0.1209		
	$\hat{\sigma}^2_{\ln y}$	0.2384			0.2013		
	$\ln(\mathcal{L})$	-12879			-12701		
Inequality	$I_R(x, z; \beta, \phi)$ Background			0.0442			0.0588
	$I_E\left(x, z; \beta, \phi, \sigma^2\right)$ Background			0.0401			0.0518
	$I_R(x, z; \beta, \phi)$ Cog/Non-C			0.0517			0.0619
	$I_E\left(x, z; \beta, \phi, \sigma^2\right)$ Cog/Non-C			0.0469			0.0546
	$I_R(x, z; \beta, \phi)$ Total			0.0958			0.1209
	$I_E\left(x, z; \beta, \phi, \sigma^2\right)$ Total			0.0869			0.1065

Note: The table presents estimates from EQ (1) including covariates capturing cognitive/non-cognitive traits. Parameters are estimated by Maximum Likelihood with cluster robust covariance. Results for annual incomes are presented on the left while estimates for permanent income are given on the right. In each case the leftmost columns give standardized regression coefficients (i.e. where all variables are z transformed) while the second columns show correlations between each variable and the dependent variable. The product of the terms is then given in the rightmost columns. These terms are then aggregated over (i) the background characteristics, (ii) the cognitive/non-cognitive variables, and (iii) the full set of covariates to give measures of relative inequality of opportunity $I_r(x, z; \beta, \phi)$ attributable to each. Multiplying these terms by the variance gives the absolute inequality of opportunity metrics $I_A\left(x, z; \beta, \phi, \sigma^2\right)$.

The results presented above show that our cognitive and non-cognitive variables are extremely important in explaining variations in living standards. For both annual and five-year incomes, cognitive skill as captured by the Symbol Digit Modality Score is the most important psychological variable. The product terms for this variable are {0.0155, 0.0186} respectively, with estimates for non-cognitive skills associated with conscientiousness {0.0123, 0.0151} next in magnitude. Agreeableness, extroversion and openness to experience have no statistically significant link with annual incomes, although the latter does negatively predict permanent incomes. Our locus of control measures are also important, with negative signs for all indicators, although the results are only significant for the variable measuring a perceived inability to confront problems {0.0122, 0.0149}. Nonetheless, summing across these indicators shows that jointly, locus of control {0.0247, 0.0259} is actually more important than either intelligence {0.0155, 0.0200} or conscientiousness {0.0123, 0.0151} in determining economic outcomes.

By aggregating the correlation weighted coefficients in this regression, we can also (i) estimate the relative contributions of psychological factors, and (ii) determine whether or not the effects of background factors are diminished in this model. Adding the coefficients down the columns, we estimate that 9.58% of annual income and 12.09% of permanent income are explained by both sets of factors - approximately double our IOP estimates from Table 1. These figures can be decomposed into contributions {0.0442 and 0.0517} for annual incomes, and {0.0558 and 0.0619} for permanent incomes, where the former is the contribution from traditional circumstances and the latter is from the psychological variables.

Two findings from this aggregation exercise are worth emphasizing. Firstly, the inequality explained by the psychological skill variables is slightly higher than that of the background variables - for our data set the contributions can be decomposed into an approximately 60:40 split. This suggests that individuals who are disadvantaged with respect to their acquisition of valuable psychological skills face a greater deficit in opportunity than those who have disadvantageous characteristics in terms of race, gender or parental social class. Given that little public attention is focused on cognitively disadvantaged individuals, it appears that these persons are under-represented in policy discussions concerning the underlying drivers of economic inequality.

Secondly, since both cognitive and non-cognitive skill development are responsive to interventions in utero and in childhood, targeted policies offer genuine scope for reducing inequalities in opportunity (Cunha and Heckman, 2009). While interventions aimed at promoting cognitive development in children are likely to be effective, these programs tend to lose potency beyond the age of 10 (Heckman, 2007). Conversely, non-cognitive traits like conscientiousness and locus of control are also partially modifiable, and remain so for longer (including into adulthood), allowing for a potentially larger aggregate impact if interventions are sustained (Cunha *et al.*, 2006). Combining this result with our relatively large effect sizes (especially for locus of control) indicates the potential for effective inequality-reducing interventions from developing this skill.

5 Path Effects and the Transmission of Psychological Traits

Path Effects

Having established some basic facts about the relative contributions of each variable type, we now use these models to explore possible transmission paths. For example, we are interested in whether factors like race or gender directly impact upon economic outcomes, or whether they act by influencing the psychological states of individuals, which then affect the income generating process (i.e. Mechanism B from Figure 1).

The mechanics are as follows: we compare estimates on background factors across our two sets of models, one containing only background characteristics, and another containing both background and cognitive/non-cognitive variables. If background characteristics only matter in that they generate valuable psychological traits, then we would expect the coefficients on these variables in income regressions to approach zero when our cognitive and non-cognitive variables are controlled for. Conversely, if background characteristics exert only direct effects upon incomes, we would expect to see the coefficients on these variables to remain constant across the two specifications. Thus, any shrinkage of the inequality attributable to background traits in the second model implies a confounding effect due to omitted psychological skills from the first estimation. As above, this requires the relatively strong assumption of zero covariance between errors from the full model and the first-stage model.

The estimates depicted in Table 2 allow us to perform such an analysis. Contrasting parameter values from Table 1 (with only traditional background variables included) with those from Table 2, we see that our inequality estimates are only slightly reduced in the presence of psychological factors. Across the two models, the estimates for annual income (omitting and including the cognitive/non-cognitive variables) are $\{0.0504, 0.0442\}$, implying that 88% of the original inequality remains once the latter are accounted for. Similarly, for permanent incomes the estimates are $\{0.0662, 0.0589\}$ which leaves 89% of the original inequality intact. Therefore the confounding effects in these models are around 11-12%, indicating that the strong majority of explained variation does not operate via psychological channels. Different mechanisms are required to explain why these disparities exist.

Nonetheless, if we turn to the individual coefficients there is evidence of some substantial parameter differences for specific variables. For example, gender does not generate significant inequalities in either annual or permanent incomes in the background-only models, but the contributions almost triple, and become significant, when psychological factors are accounted for. As we show in the next section, this is due to women having higher degrees of certain skills such as conscientiousness that are rewarded in these models (Flinn *et al.*, 2017). Similarly, the estimates in Table 1 indicate a small (but not statistically significant) benefit to being born in a non-English speaking country - a result which is surprising given that migrants are expected to experience some forms of discrimination. Nonetheless, there is evidence that as migration is typically challenging, there is an endogenous selection process whereby only more cognitively and non-cognitively skilled individuals take part (Butikofer and Peri, 2017; Caponi, 2011). Thus we see the benefit associated with this background characteristic diminish when psychological factors are taken into account. Migrancy does not bring direct advantages *per se*, but migrants are advantaged through higher levels of useful psychological traits.

Two-Part Regression Decompositions

We now consider an extension of the model presented in Section 3, however in this instance we wish to explicitly allow for the possibility that psychological traits themselves are partially inherited (a further investigation of Path B in Figure 1). This involves modelling two-part mechanisms, where traditional background characteristics partially determine our cognitive/non-cognitive variables, and both affect economic outcomes. Note that we are not trying to directly estimate the heritability of psychological traits, which would require observations on both parent and child psychological measures. Rather, the objective is to determine whether the variability in psychological traits explained by background variables is able to account for some material fraction of our inequality measures.

This approach provides two additional pieces of information that build upon the estimates above. Firstly, since we know that certain psychological traits are valuable, our decomposition highlights the inequality of opportunity in the acquisition of these traits. Thus we are able to identify which background characteristics predict greater variation in modifiable traits such as conscientiousness and locus of control. Secondly, the technique allows us to determine the extent to which the confounding effects of 11-12% established above operate via background characteristics directly influencing psychological skills.

Our econometric technique operates along similar lines to Blanden *et al.* (2007) and Mahler and Ramos (2019). Using a series of m regressions, we split each psychological variable z_l into a proportion that can be accounted for by background characteristics, z_{lE} and an proportion z_{lU} that is unexplained, such that $z_l = z_{lE} + z_{lU}$. This is done with the series of regressions

$$\widetilde{z}_l = \gamma_0 + \sum_{j=1}^{k} \gamma_j \widetilde{x}_j + \varepsilon, \qquad l = 1, ..., m \tag{8}$$

We then estimate the model below using the same distributional assumptions as in EQ (1)

$$\ln(y)^* = \alpha + \sum_{j=1}^{k} \beta_j \widetilde{x}_j + \sum_{l=1}^{m} \phi_l \left(\widetilde{z}_{lE} + \widetilde{z}_{lU}\right) + \varepsilon \tag{9}$$

Since each variable is normalized such that $\sigma_{zl} = 1$, we can exploit the property $\sigma_{zl} = \sigma_{zl}^2 = \sqrt{\sigma_{zlE}^2 + \sigma_{zlU}^2}$ and perform the decomposition below.

$$I_R(\beta, \phi, \rho) = \sum_{j=1}^{k} \hat{\beta}_j \hat{\rho}\left(\ln(y); x_j\right) + \sum_{l=1}^{m} \hat{\phi}_l \hat{\sigma}_{z_{lE}}^2 \hat{\rho}\left(\ln(y); z_l\right) + \sum_{l=1}^{m} \hat{\phi}_l \hat{\sigma}_{z_{lU}}^2 \hat{\rho}\left(\ln(y); z_l\right) \tag{10}$$

These regressions partition the explained variation in income into contributions from (i) background characteristics, (ii) cognitive/non-cognitive skills explained by background characteristics, and (iii) cognitive/non-cognitive skills that are *un*explained by background characteristics. If a psychological variable is unrelated to our set of background characteristics, then we should observe no contribution via our intermediate channel. In this instance $\hat{\sigma}_{z_{lE}}^2 = 0$ and $\hat{\sigma}_{z_{lU}}^2 = 1$, implying a flow-on estimate of zero, such that the full effect is observed through the unexplained channel. Conversely, if a psychological trait is entirely inherited, then $\hat{\sigma}_{z_{lE}}^2 = 1$ and $\hat{\sigma}_{z_{lU}}^2 = 0$, and therefore the entire channel for that trait is attributed indirectly to an individual's circumstances.

The first stage regressions attributing psychological traits to background characteristics are given in Tables 3 (cognition and locus of control) and 4 (big 5 personality traits). Combining these results with estimates in Tables 1 and 2 provides a full decomposition of the chain of effect running from background characteristics to outcomes via psychological traits.

Table 3: The Effects of Background Characteristics on Cognition and Locus of Control

Background	Cognitive		Locus of Control			
	Bds	Sdm	Can	Cont	Push	Solv
Female	-0.0044	0.1439***	0.0288	-0.0031	-0.0044	-0.0105
Migrant Non-English	0.0028	-0.0601	0.0102	0.1400***	0.1571***	0.1666***
Non-Native English Speaker	-0.0353	0.0525	0.1011**	0.0378	-0.0649	-0.0408
Arrived as Refugee	-0.0200	-0.0401*	-0.0389	-0.0446*	-0.0201	-0.0251
Father Migrated to Aust	0.0068	0.0842**	-0.0133	-0.0213	0.0159	-0.0505
Mother Migrated to Aust	0.0302	-0.0033	-0.0112	-0.0237	-0.0449	0.0084
Aboriginal or Torres Strait	-0.0402*	-0.0112	0.0441	0.0335	0.0207	0.026
Father ED Primary	-0.0537*	-0.1455***	0.0455	0.0301	0.0177	0.0322
Mother ED Primary	-0.0023	0.0163	-0.0497	-0.0184	-0.0268	-0.0014
Father ED 10 Plus	-0.0148	0.0188	-0.0195	-0.0193	-0.0108	-0.0297
Mother ED 10 Plus	0.0298	0.1061***	-0.0293	-0.0364	-0.0102	-0.003
Father Occupational Status	0.1362***	0.0912***	0.0047	-0.0598**	-0.0457	-0.0172
Mother Occupational Status	0.0484	0.0245	-0.0201	-0.0530*	-0.0550*	-0.0246
Father Unemployed at 14	0.0265	0.0707***	0.0159	0.0435*	0.0526**	0.0428
Mother Works at Age 14	0.0606**	0.0611**	-0.0124	-0.0597**	-0.0408	-0.0442*
Parents Broken Up at 14	-0.0159	0.0099	-0.015	-0.0303	-0.0012	0.0033
Constant	3.E-09	0.E+00	4.E-09	-1.E-09	-1.E-08	-2.E-8
σ_E^2	0.0458	0.1116	0.0158	0.0422	0.0209	0.0213
σ_U^2	0.9542	0.8884	0.9842	0.9578	0.9791	0.9787

Note: The table presents estimates of the effects of background characteristics on the development of cognitive/non-cognitive skills. Normalized regression coefficients are given in the rows while the columns each refer to a specific psychological variable. Bds - *Backward Digit Span*; Sdm - *Symbol Digit Modality Score*; Can - *Can Do Anything*; Cont - *Cannot Control Important Things in Life*; Push - *Feel Pushed Around*; Solv - *Cannot Solve Problems.* All regressions use cluster-robust covariance. *, ** and *** denote significance at 10%, 5% and 1% respectively.

Consistent with our result outlined above, the strongest correlations are almost invariably associated with gender. Controlling for other factors, women had higher scores in terms of cognition, agreeableness, conscientiousness and extroversion, and lower on our openness to experience metric. Given that these traits are all predictive of better economic outcomes, our null results on the impact of gender in Table 1 therefore represent the net effects of two offsetting causal flows. The first is an explained effect (of magnitudes given in Table 2) and operates through greater concentrations of these psychological skills. The second effect is unexplained by our model and approximately equal in size to the first. This is a negative effect, correlated with gender but not other circumstances or psychological variables, and plausibly the result of discrimination or gender-based differences in preferences.[21] Since these skills are likely to be rewarded differently in labor markets and educational institutions, the asymmetries may explain the interactive effects between gender and parental background found by Brenøe and Lundberg (2018).

[21]See the estimates in Tables 6 and 7 and the surrounding discussion for more on this point.

Table 4: The Effects of Background Characteristics on the Big Five Personality Traits

Cog/Non-Cog	Agree	Conc	Stab	Extrv	Open
Female	0.2708***	0.1126***	0.0100	0.0815***	-0.0519**
Migrant Non-English	-0.0194	-0.0419	-0.0466	-0.0478	0.0065
Non-Native English Speaker	-0.0455	0.0832*	0.0018	0.0004	-0.0355
Arrived as Refugee	-0.0011	-0.0085	-0.0328	-0.0225	0.0121
Father Migrated to Aust	0.0336	0.0495	0.0184	0.0654*	0.0653*
Mother Migrated to Aust	0.0516	0.0191	0.0515	-0.0225	-0.0016
Aboriginal or Torres Strait	-0.0523*	-0.0146	0.0161	-0.0215	-0.0609**
Father ED Primary	-0.0109	0.0053	0.0446	0.0176	0.0039
Mother ED Primary	0.0116	0.0017	0.0396	0.0548*	-0.0115
Father ED 10 Plus	-0.0158	-0.0034	-0.0093	0.0137	0.0341
Mother ED 10 Plus	-0.0132	0.0284	0.0004	0.0572*	-0.0192
Father Occupational Status	-0.0054	-0.0247	0.0262	0.0026	0.0909***
Mother Occupational Status	-0.0265	0.0013	0.0039	0.0033	0.0692**
Father Unemployed at 14	-0.0069	-0.0496*	-0.0710***	-0.0134	0.0222
Mother Works at Age 14	-0.0412*	-0.0121	-0.0787***	0.0179	-0.0227
Parents Broken Up at 14	-0.0262	0.0462*	-0.0097	0.0413	0.0068
Constant	3.E-09	-6.E-09	3.E-09	2.E-09	4.E-09
σ_E^2	0.0834	0.0261	0.0222	0.0189	0.0328
σ_U^2	0.9166	0.9739	0.9778	0.9811	0.9672

Note: The table presents estimates of the effects of background characteristics on the development of cognitive/non-cognitive skills. Normalized regression coefficients are given in the rows while the columns each refer to a specific psychological variable. Agree - *Agreeableness*; Conc - *Conscientiousness*; Stab - *Emotional Stability*; Extr - *Extroversion*; Open - *Openness to Experience*. All regressions use cluster-robust covariance. *, ** and *** denote significance at 10%, 5% and 1% respectively.

Of the other circumstance variables, our markers of parental socioeconomic status had the strongest path-effects. As well as impacting directly upon outcomes, these variables operate partially by driving both better cognitive development (a result that holds over both intelligence indicators), and a stronger locus of control. As these traits are well known to assist in the accumulation of human capital, transmission via greater scope for education or skill development is highly plausible (Suhonen and Karhunen, 2019). Interestingly however, persons from higher status parents also had higher levels of openness to experience, a variable which significantly predicts *poorer* economic outcomes. One possible explanation is that risk-taking behavior associated with openness (McGhee *et al.*, 2012) in families of higher socioeconomic rank might actually play a mitigating role. That is, preferences for heterogeneous life-experiences are correlated with parental socioeconomic status, and also act to lower economic wellbeing, forming a causal channel that reduces the intergenerational transmission mechanism. Lastly, challenging life experiences during childhood also generate inequality in opportunity by lowering emotional stability during adulthood. Therefore, childhood stress, a known predictor of various anxiety and depressive symptoms (Moskvina *et al.*, 2007), creates an additional plausible explanatory path.

However, despite these findings, the central conclusion from Tables 3 and 4 is that the links between cognitive/non-cognitive skills and background characteristics are quite weak. In most cases, the background variables only account for around 2-3% of the variation in the psychological measures, although for cognition (as measured by the SDM score) this value is around 11%. Thus while there appears to be greater pre-determination in intelligence than in personality, the strong majority variation in all psychometric measures are left unexplained. The first parts of the two-stage mechanisms in Figure 1 therefore have little explanatory power, consistent with our small path estimates above.

Flow-On Effects

To obtain estimates of these flow-on effects, we present the decomposition in EQ (6) in Table 5 (annual income) and Table 6 (five-year income) below. In each instance, the marginal effect from EQ (1) is given alongside the correlation coefficient ρ_{yj}, however for our cognitive/non-cognitive skills we also include the explained and unexplained components $\hat{\sigma}^2_{z_{lE}}$ and $\hat{\sigma}^2_{z_{lU}}$. The results are then aggregated in the bottom rows to provide (i) the direct estimate associated with background characteristics, (ii) the effect of psychological traits than can be explained by background characteristics, and (iii) the unexplained effect of psychological traits.

Table 5: Ex Ante Inequalities of Opportunity: - Background Characteristics and Cognitive/Non-Cognitive Skills

		Annual Income $\ln(y_{it}^{*})$					
Variable		$\hat{\beta}_j/\hat{\phi}_l$	$\hat{\sigma}^2_{z_{lE}}$	$\hat{\sigma}^2_{z_{lU}}$	$\hat{\beta}_j\hat{\rho}_{yj}$	$\hat{\phi}_l\hat{\sigma}^2_{z_{lE}}\hat{\rho}_{yl}$	$\hat{\phi}_l\hat{\sigma}^2_{z_{lU}}\hat{\rho}_{yl}$
Background	Female	-0.0541**			0.0009		
	Migrant Non-English Country	-0.0839*			0.0029		
	Non-Native English Speaker	0.0095			-0.0002		
	Arrived as Refugee	-0.0150			0.0005		
	Father Migrated to Aust	0.0316			0.0006		
	Mother Migrated to Aust	-0.0164			-0.0001		
	Aboriginal or Torres Strait Is.	-0.0336			0.0018		
	Father Ed Primary	0.0132			-0.0007		
	Mother Ed Primary	0.0347			-0.0014		
	Father Ed 10 Plus	0.0575**			0.0078		
	Mother Ed 10 Plus	0.0284			0.0035		
	Father Occupational Status	0.0925***			0.0150		
	Mother Occupational Status	0.0627***			0.0082		
	Father Unemployed at Age 14	-0.0581***			0.0041		
	Mother Works at Age 14	0.0162			0.0006		
	Parents Broken Up at Age 14	-0.0270			0.0006		
Cognitive	Backward Digit Span	0.0007	0.0458	0.9542	0.0000	2.0E-06	4.2E-05
	Symbol Digit Modalities	0.1027***	0.1116	0.8884	0.0155	1.7E-03	0.0137
Personality	Agreeableness	0.0327	0.0834	0.9166	0.0009	7.8E-05	0.0009
	Conscientiousness	0.0979***	0.0261	0.9739	0.0123	3.2E-04	0.0120
	Emotional Stability	-0.0500**	0.0222	0.9778	-0.0016	-3.5E-05	-0.0015
	Extraversion	-0.0160	0.0189	0.9811	-0.0004	-7.2E-06	-0.0004
	Openness to Experience	-0.0478	0.0328	0.9672	0.0003	8.7E-06	0.0003
Loc of Con	Can Do Anything - R	-0.0103	0.0158	0.9842	0.0010	1.5E-05	0.0009
	Cannot Change Things	-0.0426	0.0422	0.9578	0.0074	3.1E-04	0.0070
	Feel Pushed Around	-0.0276	0.0209	0.9791	0.0041	8.6E-05	0.0040
	Cannot Solve Prob	-0.0734**	0.0213	0.9787	0.0122	2.6E-04	0.0119
Misc	Constant	-3.16E-10					
	n	9,411					
	R^2	0.0958					
	$\hat{\sigma}^2_{\ln y}$	0.2384					
Inequality	$I_R(x,z;\beta,\phi)$ Total				0.0958	0.0028	0.0489
	$I_E\left(x,z;\beta,\phi,\sigma^2\right)$ Total				0.0228	0.0007	0.0117

Note: The table gives inequality of opportunity estimates based on both background characteristics and cognitive/non-cognitive traits. The first column gives parameter estimates from EQ (1) as per Table 2. The second and third columns present the proportion of each cognitive trait that is explained (i.e. $\sigma^2_{z_{lE}}$) and not explained ($\sigma^2_{z_{lU}}$) by the background characteristics. The fourth column weights the regression coefficients by their correlations with the dependent variable as in EQ (2) while the fifth and sixth columns decompose the overall psychological effect into explained and unexplained components. Aggregating down the columns gives the inequality of opportunity estimates $I_r(x,z;\beta,\phi)$ and $I_A\left(x,z;\beta,\phi,\sigma^2\right)$ and the contributions attributable to $\sigma^2_{z_{lE}}$ and $\sigma^2_{z_{lU}}$. Note that these are exhaustive - i.e. $\sigma^2_{z_{lE}}+\sigma^2_{z_{lU}}=1$ and hence the results are interpreted in terms of proportional shares. All regressions use cluster-robust covariance. *, ** and *** denote significance at 10%, 5% and 1% respectively.

As we would expect, the results from Table 4 indicate that the links between background characteristics and psychological skills are unable to account for a meaningful fraction of inequality of opportunity. The key estimates appear in the last three columns. Here $\hat{\beta}_j\hat{\rho}(\ln(y);x_j)$ gives the total contribution to inequality, while $\hat{\phi}_l\hat{\sigma}^2_{z_{lE}}\hat{\rho}(\ln(y);z_l)$ and $\hat{\phi}_l\hat{\sigma}^2_{z_{lU}}\hat{\rho}(\ln(y);z_l)$ give the explained and unexplained components for the cognitive/non-cognitive variables (note that the latter two terms sum to give the former). Initially we look at the annual income values in the leftmost columns. Summing the components breaks down the inequality estimates attributable to each of the vertices in Panel B of Figure 1. The overall IOP estimate remains the same at 0.0958, as does the contribution from traditional background characteristics of 0.0442. However, the contribution associated with cognitive/non-cognitive skills of 0.0517 is composed almost entirely of the direct effect of 0.0489, rather than the explained effect of 0.0028. Taking the ratio of these terms shows that the correlations between psychological skills and background characteristics only explains 5.7% of the aggregate psychological effect, and 2.9% of the total effect.

We can reconcile these results with the estimates presented in Section 3. The reduction in the estimated inequality associated with the inclusion of psychological factors was 0.0063 (corresponding to the reported 12% mediating effect), and hence around 44% of this reduction (0.0028/0.0063) is explained by the direct inheritance of psychological traits. Thus, combining these results shows us that only a small fraction of traditional inequality of opportunity estimates reflect confounding via psychological factors, and close to half of this confounding is removed once the direct heritability of valuable traits is considered.

Table 6: Ex Ante Inequalities of Opportunity: - Background Characteristics and Cognitive/Non-Cognitive Skills

		Five-Year Income $\ln(y_{it})^{**}$					
Variable		$\hat{\beta}_j/\hat{\phi}_l$	$\hat{\sigma}^2_{z_{lE}}$	$\hat{\sigma}^2_{z_{lU}}$	$\hat{\beta}_j\hat{\rho}_{yj}$	$\hat{\phi}_l\hat{\sigma}^2_{z_{lE}}\hat{\rho}_{yl}$	$\hat{\phi}_l\hat{\sigma}^2_{z_{lU}}\hat{\rho}_{yl}$
Background	Female	-0.0639***			0.0015		
	Migrant Non-English Country	-0.0993**			0.0043		
	Non-Native English Speaker	0.0026			-0.0001		
	Arrived as Refugee	-0.0172			0.0007		
	Father Migrated to Aust	0.0504			0.0014		
	Mother Migrated to Aust	-0.0234			-0.0002		
	Aboriginal or Torres Strait Is.	-0.0473*			0.0033		
	Father Ed Primary	0.0240			-0.0013		
	Mother Ed Primary	0.0321			-0.0014		
	Father Ed 10 Plus	0.0744***			0.0114		
	Mother Ed 10 Plus	0.0182			0.0024		
	Father Occupational Status	0.1016***			0.0183		
	Mother Occupational Status	0.0768***			0.0113		
	Father Unemployed at Age 14	-0.0613***			0.0047		
	Mother Works at Age 14	0.0189			0.0008		
	Parents Broken Up at Age 14	-0.0442**			0.0017		
Cognitive	Backward Digit Span	0.0164	0.0458	0.9542	0.0014	6.4E-05	0.0013
	Symbol Digit Modalities	0.1112***	0.1116	0.8884	0.0186	0.0021	0.0166
Personality	Agreeableness	0.0364	0.0834	0.9166	0.0010	8.3E-05	0.0009
	Conscientiousness	0.1118***	0.0261	0.9739	0.0151	0.0004	0.0148
	Emotional Stability	-0.0614**	0.0222	0.9778	-0.0017	-3.7E-05	-0.0016
	Extroversion	-0.0206	0.0189	0.9811	-0.0004	-7.5E-06	-0.0004
	Openness to Experience	-0.0647***	0.0328	0.9672	0.0008	2.5E-05	0.0007
Loc of Con	Can Do Anything - R	-0.0124	0.0158	0.9842	0.0012	1.9E-05	0.0012
	Cannot Change Things	-0.0515	0.0422	0.9578	0.0095	0.0004	0.0091
	Feel Pushed Around	-0.0100	0.0209	0.9791	0.0015	3.1E-05	0.0015
	Cannot Solve Prob	-0.0842**	0.0213	0.9787	0.0149	0.0003	0.0146
Misc	Constant	-0.0007					
	n	9,377					
	R^2	0.1209					
	$\hat{\sigma}^2_{\ln y}$	0.2013					
Inequality	$I_R(x,z;\beta,\phi)$ Total				0.1209	0.0034	0.0587
	$I_E\left(x,z;\beta,\phi,\sigma^2\right)$ Total				0.0243	0.0007	0.0118

Note: The table gives inequality of opportunity estimates based on both background characteristics and cognitive/non-cognitive traits. The first column gives parameter estimates from EQ (1) as per Table 2. The second and third columns present the proportion of each cognitive trait that is explained (i.e. $\sigma^2_{z_{lE}}$) and not explained ($\sigma^2_{z_{lU}}$) by the background characteristics. The fourth column weights the regression coefficients by their correlations with the dependent variable as in EQ (2) while the fifth and sixth columns decompose the overall psychological effect into explained and unexplained components. Aggregating down the columns gives the inequality of opportunity estimates $I_r(x,z;\beta,\phi)$ and $I_A\left(x,z;\beta,\phi,\sigma^2\right)$ and the contributions attributable to $\sigma^2_{z_{lE}}$ and $\sigma^2_{z_{lU}}$. Note that these are exhaustive - i.e. $\sigma^2_{z_{lE}}+\sigma^2_{z_{lU}}=1$ and hence the results are interpreted in terms of proportional shares. All regressions use cluster-robust covariance. *, ** and *** denote significance at 10%, 5% and 1% respectively.

To illustrate that the results in Table 5 are not driven by idiosyncrasies associated with annual income, the same analysis for five-year incomes appears in Table 6. As above, the permanent inequality of opportunity estimate is higher in both relative and absolute terms (0.1209 and 0.0243 respectively). The proportional inequality explained by the psychological variables is 0.0621, which is composed of an explained component of 0.0587 and an unexplained component of 0.0034. In terms of percentages, approximately 5.8% of the psychological effect is due to traits explained by background characteristics - a figure which corresponds almost perfectly with the estimate based upon annual incomes. Relative to the total (i.e. 0.0034/0.1209) we find again that only about 2.8% of the aggregate inequality of opportunity estimate is represented by this phenomenon, and again the fact that cognitive/non-cognitive skills are partially determined by background characteristics removes about half (0.0034/0.0611) of the already small path effect.

Since the distribution of valuable cognitive/non-cognitive traits does not explain the IOP estimates that appear in Section 3, then some other mechanism must explain the results. In order to understand why race, gender and social class predict certain economic outcomes, we require explanations that are (i) correlated with these circumstances, (ii) uncorrelated with cognitive/non-cognitive skills, and (iii) omitted from the models. There are several logical candidates. As above, the clearest is simply the presence of discrimination - for example labor earnings (an important input into household income) could be affected if employers exhibit racial, gender or class preferences in hiring. Bias of this general form is often regarded as pervasive (Pager and Shepherd, 2008), and would account for both the direct IOP results, and the minimal indirect estimates above. Empirical evidence along these lines is widespread - for example, resume audit studies (field experiments that manipulate characteristics of applicant CVs) reliably find patterns of discrimination that are highly consistent with our results (Bertrand and Mullainathan, 2004; Rivera and Tilcsik, 2016). A second possibility is that there may be subtle differences in factors like risk preferences and labor supply across population subgroups. If correlated with circumstances like parental socioeconomic status, these factors may also account for part of our findings (e.g. Croson and Gneezy, 2009; Manstead, 2018). While inequalities due to differing preferences are less objectionable than those from discrimination, correlations between preferences and background characteristics imply that they are also at least partially pre-determined, and therefore could be characterized as sources of unequal opportunity (Jusot *et al.*, 2013).

6 Allowing for Heterogeneous Effects

A third way that psychological variables might affect the transmission of inequality is by modifying the returns to background characteristics (i.e. Channel C in Figure 1). There are two key ideas which we examine. Firstly we test the possibility that some individuals might be sufficiently skilled such that they can overcome any inherited disadvantages. It is plausible, for example, that highly skilled individuals can reach a point where they are no longer affected by adverse circumstances. Such a result could occur, for example, if psychologically able individuals endogenously select into professions, educational groups or social spheres that do not penalize according to background traits.[22] In such an instance, strong cognitive/non-cognitive skills are not compensating or offsetting other inherited (dis)advantages, rather these traits are allowing for the effects of circumstances to be fully overcome. In this section we test for such a phenomenon by seeing whether there exists within our dataset a subgroup of our population (defined by cognitive/non-cognitive skills) within which the inequality explained by circumstances is zero.

Secondly, we also explore the idea is that even if background characteristics matter for all individuals, the heterogeneity in this process is informative about why particular circumstances exhibit specific effects. If certain background characteristics matter more for some personality types than others, this heterogeneity provides additional clues as to how inherited disadvantages manifest themselves.

To allow persons with differing psychological profiles to respond heterogeneously to their circumstances, we employ finite mixtures of the regression models specified above. Stacking our circumstance and psychological variables into $k \times 1$ and $m \times 1$ vectors $\mathbf{x}$ and $\mathbf{z}$, and defining the distribution of our income variable as $f(\ln y)$, we specify the model

$$f(\ln y|\mathbf{x}, \mathbf{z}; \boldsymbol{\beta}, \boldsymbol{\phi}, \boldsymbol{\gamma}) = \sum_{u=1}^{v} p_u(\mathbf{z}; \boldsymbol{\phi}) f_u\left(\ln y; \mathbf{x}_u^{'}\boldsymbol{\beta}_u, \boldsymbol{\gamma}_u\right) \tag{11}$$

As above each $f_u(\ln y) = \varphi(.)$ is normal, and the $u = 1, ..., v$ latent classes reflect endogenously determined subgroups, each of which characterize a differing psychological profile. Membership of these groups is probabilistic $p_u(\mathbf{z}; \boldsymbol{\phi})$ and depends upon cognitive and non-cognitive traits $\mathbf{z}$, and the parameter vector $\boldsymbol{\phi}$. Here $0 < p_{ui}(\mathbf{z}_i; \boldsymbol{\phi}) < 1$ where a logistic specification is used to constrain our class probabilities to the $(0, 1)$ interval, such that $\sum_{u=1}^{v} p_{ui}(\mathbf{z}_i; \boldsymbol{\phi}) = 1$ for both $i = 1, ..., n$ and $u = 1, ..., v$. In principle, the number of classes v should reflect the number of distinct clusters of personality traits that modify the effects of $\mathbf{z}$. However, given the limitations on the size of our data set we simplify and set $v = 3$ as per the AIC. The subgroups have their own parameter vector $\boldsymbol{\beta}_u$ which measures the effect of background characteristics within that group. Lastly, the variance and intercept term for each regression are included within $\boldsymbol{\gamma}_u$. The model is estimated via maximum likelihood using the Newton-Raphson algorithm.

[22]E.g. a non-native English speaker might experience more disadvantage as a manual worker than in a professional sector.

Table 7: Ex Ante Inequalities of Opportunity Allowing for Heterogeneity According to Cog/Non-Cog Skills

	Annual Income $\ln(y^*_{it})$			Latent Class Predictors		
Background	$\hat{\boldsymbol{\beta}}_1$	$\hat{\boldsymbol{\beta}}_2$	$\hat{\boldsymbol{\beta}}_3$	Cog/Non-Cog	$\hat{\boldsymbol{\phi}}_2$	$\hat{\boldsymbol{\phi}}_3$
Female	0.0140	-0.1124**	-0.0126	Backward Digit Span	-0.0863	0.0181
Migrant Non-English	-0.1667**	-0.0379	-0.1032***	Symbol Digit Mod	0.4867***	0.5912***
Non-Native English	0.0402	-0.0498	0.0365	Agreeableness	0.1938**	0.2375***
Arrived as Refugee	-0.0294	0.1002**	-0.1007***	Conscientiousness	0.3268***	0.5893***
Father Migrated to Aust	0.0357	0.0283	0.0203	Emotional Stability	-0.3809***	-0.3922***
Mother Migrated to Aust	-0.0635	0.0152	-0.0118	Extroversion	0.0411	-0.0456
Aboriginal or Torres St	-0.0355	-0.0685***	-0.0039	Openness to Exp	-0.4967***	-0.3861***
Father Ed Primary	-0.0603	0.2752***	-0.1903***	Can Do Anything - R	-0.4364***	-0.1867***
Mother Ed Primary	0.0120	0.1102***	-0.0284	Cannot Change Things	0.0088	-0.1543
Father Ed 10 Plus	-0.0206	0.0800***	0.1109**	Feel Pushed Around	-0.1923**	-0.1659**
Mother Ed 10 Plus	0.1030**	0.0164	-0.0075	Cannot Solve Prob	-0.2386**	-0.4427***
Father Occupational Stat	0.0321	0.1317***	0.0562***			
Mother Occupational Stat	0.0560	0.0709***	0.0813***			
Father Unemployed at 14	-0.1270***	-0.0158	-0.0639***			
Mother Works at Age 14	0.0063	0.1061	-0.0524**			
Parents Broken Up at 14	0.0574	-0.0606	-0.0570***			
Constant	-0.8986***	-0.1799	0.5434*		1.1525***	1.1935***
$\bar{p}_j(\mathbf{z};\boldsymbol{\phi})$ Prior	17.91%	39.27%	42.82%			
$\hat{\sigma}^2$	1.334	0.4240	0.3990			
$I_R(x,z;\beta,\phi)$	0.0446	0.0457	0.0555	$\ln\mathcal{L}\left(\beta,\phi,\sigma^2\right)$	-12524	

Note: The table presents estimates from the finite mixture model specified in EQ (6) where annual incomes are the dependent variable. Estimates in the leftmost three columns present the effects of background characteristics on incomes for individuals in subgroup u. Estimates in the two right-hand columns correspond to a multinomial logit model assigning probabilities to belongingness to a given subgroup. Here subgroup 1 is the base class, and positive numbers indicate a greater probability of belonging to the given class. Again all mixing components are normal with means $\mathbf{x}'\beta$ and variances σ^2_u. The averaged class probabilities are given as $\bar{p}_u(\mathbf{z};\boldsymbol{\phi})$ Prior. *, ** and *** denote significance at 105, 5% and 1% respectively.

The models depicted in Tables 7 and 9 present the estimations for each of our income variables. In both cases there is an attractive symmetry to the ways that the latent classes are formed. *Class 1* (the reference class) is the least cognitively skilled of our three groups. As per the signs and magnitudes of the estimates in the equations $p_u(\mathbf{z};\boldsymbol{\phi})$, higher scores on both the Backward Digit Span and Symbol Digit Modality test predict membership to *Class 2*, or *Class 3*. If we turn to other psychological traits that predict higher incomes (from Table 2), we see the same pattern for Conscientiousness, Agreeableness, Emotional Stability, and also our measures of Locus of Control. Thus we are observing a clustering of psychological characteristics where individuals with valuable cognitive/non-cognitive skills are endogenously grouped, with *Class 3* having the strongest set, and *Class 2* forming an intermediate group.

To provide an intuitive guide of the psychological nature of the groups, we present an ordinal classification on each criterion in Table 8. Attractively, each of the subgroups capture a substantial share of the sample. When looking at annual incomes, the probability weights for *Class 1* indicate that it accounts for around 18% of our data set, while results for *Class 2* and *Class 3* are approximately 39% and 42% respectively. When permanent incomes are the dependent variable *Class 1* is approximately 14%, with *Class 2* making up 63% and *Class 3* around 23%.

Table 8: Ordinal Description of Cog/Non-Cog Subgroup Types: - Annual and Permanent Income Models

	Annual Income			Permanent Income		
Cog/Non-Cog Skill	Subgroup 1	Subgroup 2	Subgroup 3	Subgroup 1	Subgroup 2	Subgroup 3
Intelligence	Low	Medium	High	Low	Medium	High
Locus of Control	Low	Medium	High	Low	Medium	High
Agreeableness	Low	Medium	High	Low	High	Medium
Conscientiousness	Low	Medium	High	Low	Medium	High
Emotional Stability	High	Medium	Low	High	Low	Medium
Extraversion	Medium	High	Low	High	Medium	Low
Openness to Exp	High	Low	Medium	High	Low	Medium

Note: The table presents ordinal labeled on the personality characteristics of each latent subgroup. In the instances when there are compound indicators (intelligence, locus of control) we use an equal-weighted sum of the relevant variables to determine the ordering.

Turning to the estimates for $\boldsymbol{\beta}_u$ for $u = 1, ..., 3$ in Table 7 we see that there are substantial effect sizes associated with our traditional background variables over all three classes. For example, our indicator for gender (female) accounts for a reduction in income of approximately 10% for individuals with moderate cognitive/non-cognitive skills, but doesn't appear to confer economic disadvantage for individuals in the higher or lower subgroups. A similar result also holds for our indicator of indigenous heritage. In some instances our model exhibits some collinearity issues - for example refugee status predicts significant reductions for persons in *Class 3* but an approximately offsetting increase in income for *Class 2*. In such a case it is likely that there is some heterogeneity in the ways that more cognitively able individuals are impacted, but that the net effect for the groups combined is close to zero.

In line with the results presented above, the strongest and most robust predictors of lower incomes are those related to parental social class. Greater parental education predicts much better outcomes for the more psychologically able individuals in *Class 2* or *Class 3* than *Class 1*, as do the both maternal and paternal socioeconomic/occupational status measures. Such a result makes sense if a certain amount of cognitive or non-cognitive skill is required to benefit from the types of investments usually made by richer or better educated parents (Anderson and Leo, 2009). Thus, it is the simultaneous presence of an advantageous background and beneficial psychological traits that appears to matter. Since both sets of variables plausibly drive educational success (e.g. Lundberg, 2013), this result is consistent with our earlier finding - that unequal abilities to accumulate human capital may be a key factor. Notably, our estimates imply that this effect would generate inequalities primarily in the higher ends of our income distribution, where advantageous traits are more highly concentrated. The fact that parental economic status matters a little less in *Class 1* may be due to the absence of this effect - incomes in these groups are likely to be disproportionately set by governments, either through social safety nets or minimum wage legislation, and therefore less responsive to background factors that predict human capital development. However, persons in *Class 1* seem to be a little more sensitive to our ancestral variables. Effect sizes for both maternal and paternal migrancy are largest for this group (across both models), as does our indicator of being born in a non-English speaking country.

As per the regression results in Table 2, there is also some evidence that paternal class matters a little more than maternal class. Fathers that have a Year 10 education or greater, or higher occupational status scores, seem to confer a little more advantage than the corresponding maternal scores for more cognitively/non-cognitively able individuals. Again this result may reflect a resource-effect. Since paternal socioeconomic status is more predictive of family income than maternal status (due to higher levels of male labor supply), we may be picking up the same interaction between psychological skill and social class outlined above. Alternatively, it is also possible that paternal economic status has a stronger effect on shaping attitudes (and hence behaviors) than maternal status. In such an instance, fathers' educational and occupational status might set their children's economic ambitions, which may only be realized when combined with a sufficient level of cognitive/non-cognitive skill. Nonetheless, empirical evidence on this phenomenon is mixed (Cabrera *et al.*, 2011) and therefore the strength of any expectations effect is uncertain.

Table 9: Ex Ante Inequalities of Opportunity Allowing for Heterogeneity According to Cog/Non-Cog Skills

	Permanent Income $\ln(y_{it}^{**})$			Latent Class Predictors		
Background	$\hat{\boldsymbol{\beta}}_1$	$\hat{\boldsymbol{\beta}}_2$	$\hat{\boldsymbol{\beta}}_3$	Cog/Non-Cog	$\hat{\boldsymbol{\phi}}_2$	$\hat{\boldsymbol{\phi}}_3$
Female	-0.0082	-0.1022***	0.0690*	Backward Digit Span	0.0565	0.1642*
Migrant Non-English	-0.2442***	-0.0735**	-0.1852***	Symbol Digit Mod	0.6785***	0.9047***
Non-Native English	0.0099	-0.0128	0.0677	Agreeableness	0.3684***	0.3382***
Arrived as Refugee	-0.0657	0.0528***	-0.1314***	Conscientiousness	0.4881***	1.1182***
Father Migrated to Aust	0.1356**	0.0616**	-0.0296	Emotional Stability	-0.6484***	-0.5909***
Mother Migrated to Aust	-0.0861	-0.0190	0.0219	Extroversion	-0.0376	-0.2452***
Aboriginal or Torres St	-0.0527	0.0093	-0.2857***	Openness to Exp	-0.7164***	-0.6359***
Father Ed Primary	0.0082	0.1030***	-0.1836***	Can Do Anything - R	-0.5447***	-0.1453
Mother Ed Primary	-0.0502	0.0820***	-0.0660*	Cannot Change Things	-0.0447	-0.5765**
Father Ed10 Plus	0.0617	0.0323*	0.2683***	Feel Pushed Around	-0.1340	-0.0180
Mother Ed 10 Plus	0.0727	0.0077	-0.0246	Cannot Solve Prob	-0.5159**	-0.5951***
Father Occupational Stat	0.0584	0.1539***	-0.0105			
Mother Occupational Stat	0.1288**	0.0917***	0.0232			
Father Unemployed at 14	-0.0736*	-0.0585***	-0.0541			
Mother Works at Age 14	0.0277	0.0785***	-0.1398***			
Parents Broken Up at 14	-0.0206	-0.0805***	0.0011			
Constant	-0.9859***	0.0315	0.5442**		2.2476***	0.9530
$\bar{p}_u(\mathbf{z};\boldsymbol{\phi})$ Prior	14.36%	63.17%	22.47%			
$\hat{\sigma}^2$	1.120	0.6427	0.3817			
$I_R(x,z;\beta,\phi)$	0.0783	0.0596	0.0894	$\ln\mathcal{L}\left(\beta,\phi,\sigma^2\right)$	-12418	

Note: The table presents estimates from the finite mixture model specified in EQ (6) where five-year incomes are the dependent variable. Estimates in the leftmost three columns present the effects of background characteristics on incomes for individuals in subgroup u. Estimates in the two right-hand columns correspond to a multinomial logit model assigning probabilities to belongingness to a given subgroup. Here subgroup 1 is the base class, and positive numbers indicate a greater probability of belonging to the given class. Again all mixing components are normal with means $\mathbf{x}'\beta$ and variances σ_u^2. The averaged class probabilities are given as $\bar{p}_u(\mathbf{z};\boldsymbol{\phi})$ Prior. *, ** and *** denote significance at 105, 5% and 1% respectively.

While it is clear that psychological skills modify the effects of certain background characteristics, we are also interested in whether the aggregate effects are systematically modified across our groups. To establish this, we reconstruct the inequality estimates in EQ (2) by multiplying the standardized estimates by the correlations with the dependent variable, where the latter reflect the means of individual class probabilities. These results are reported in the final rows of Tables 7 and 9. If predetermined factors do not create inequalities of opportunity for individuals with particular sets of cognitive/non-cognitive skills, then we expect to see estimates of $I_r(x,z;\beta,\phi)$ go to zero for that class. Or if having the right psychological traits helps individuals partially overcome inherited adversity, we would anticipate seeing substantially reduced estimates for that class. Looking at annual incomes, our estimates of inequality of opportunity for individuals in the three classes are {0.0446; 0.0457; 0.0555}, which are comparable in magnitude for the original inequality estimate that ignores heterogeneity in effects of {0.0504}. For permanent incomes, we observe background inequality estimates of {0.0783; 0.0596; 0.0894}, which as a probability-weighted average are a little higher than the baseline estimate from the pooled sample of 0.0662 from Table 1. None of these estimates approach zero, and there is no systematic pattern where inequality estimates are lower for a particular group. Indeed, the only discernible pattern is that traditional background characteristics are slightly more important for psychologically skilled individuals. Thus the idea that sufficient cognitive/non-cognitive skill erases the impacts of adverse inherited circumstances is rejected - all individuals are advantaged or disadvantaged by their set of inherited (traditional) background characteristics.

7 Conclusion

We now return to the issues raised in the introduction - how much inequality in Australia is pre-determined, and what roles do cognitive/non-cognitive skills play in the emergence of this inequality? Initially, our baseline estimates showed that explained inequality in household disposable income is quite low. If we restrict our set of circumstances to traditional background characteristics, then only around 5-6% of the total variation in incomes is explained, leaving the remaining 94-95% to factors such as efforts, unobserved circumstances and data/econometric issues such as measurement and specification error. However, this breakdown ignores the fact that personal characteristics related to intellect and temperament are also largely inherited, and therefore could be treated as additional neglected circumstances. Including these factors into our models more than doubles our IOP estimates, indicating that psychological traits (particularly cognitive skill as captured by the Symbol Digit Modality test, and non-cognitive skills associated with conscientiousness and locus of control) are at least as important as factors such as race, class and gender. Therefore, if regarded as pre-determined, these psychological variables represent a large and relatively unexplored source of illegitimate inequality. Policy interventions that aid their development at the lower end of the income distribution therefore offer genuine scope for mitigating harmful inequalities. When coupled with empirical evidence on the longer-term malleability of locus of control, our estimates suggest that targeting this trait in particular could be highly beneficial.

We also showed that psychological skills are also partially dependent upon an individual's background, which forms an intermediate channel through which circumstances affect outcomes. In some instances these cognitive/non-cognitive variables mask inequalities arising from other sources. For example, women and children from migrant families are disadvantaged in our income equations. However they also tend to score better on traits like conscientiousness and locus of control, which are valuable in our main models. Small inequalities associated with gender and family background therefore widen once these intermediate factors are accounted for. Children from high SES fathers also develop stronger cognitive skills, which partially explain why they have better outcomes in standard models.

Despite these empirical links, our results also indicate that cognitive and non-cognitive variables only account for a small share of traditional IOP estimates. We showed that including psychological factors in models of the intergenerational transmission channel only decreases estimates associated with standard background characteristics by 11-12%. Thus, the idea that inequalities attributed to immutable personal characteristics simply reflect psychological traits that are usually excluded from such an analysis is not well supported. Since differences in psychological skills *do not* account for a particularly meaningful share of IOP, then our estimates must therefore emerge primarily via different channels. Social factors correlated with circumstances but omitted from the models (such as discrimination and differing preferences) represent logical candidates for explaining the majority of circumstance-based disparity.

Lastly, we considered the possibility that cognitive and non-cognitive skills might affect the transmission of economic status by modifying the effects of other background characteristics. We uncovered ample evidence that this is the case - across latent classes there was substantial heterogeneity in the ways that individuals with different skill levels responded to inherited (dis)advantage. For instance, strong psychological traits were even more beneficial when mixed with markers of higher parental socioeconomic status. Nonetheless, in aggregate terms we found little to suggest that individuals with high levels of advantageous cognitive/non-cognitive traits were able to overcome their backgrounds. As the total effects of background characteristics are similar across psychological classes, it appears that all persons are advantaged or disadvantaged by their immutable birth characteristics, regardless of their psychological traits.

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Appendix

A1 Descriptive Statistics - All Variables

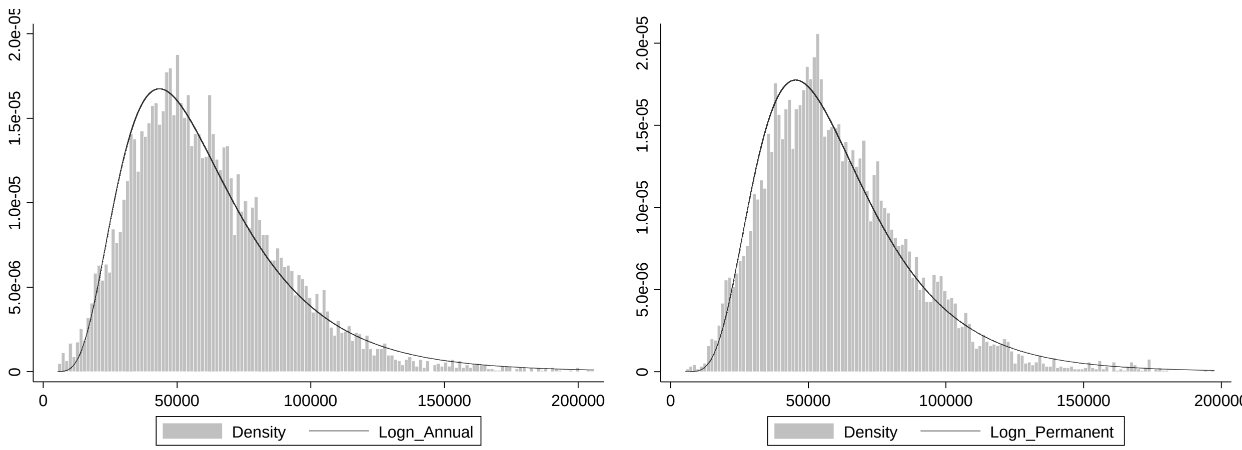
Descriptive statistics of our sample are presented below. Income is presented in logarithmic form, although densities for the original values are depicted in Figure 2.

Table 10: Descriptive Statistics - All Variables - Imputed Sample

Variable Type	Variable Name	n	$\bar{x}$	$\hat{\sigma}$	Min	Max
Income	Annual Income - $\ln(y_{it}^{*})$	9,411	10.915	0.4882	8.6012	12.2348
	Permanent Income - $\ln(y_{it}^{**})$	9,377	10.922	0.4487	8.5915	12.1933
Background	Female	9,411	0.533	0.4990	0	1
	Immigrant Non-English Country	9,411	0.135	0.3416	0	1
	Non-Native English Speaker	9,411	0.110	0.3133	0	1
	Arrived as Refugee	9,411	0.008	0.0889	0	1
	Father Migrated to Aust	9,411	0.395	0.4888	0	1
	Mother Migrated to Aust	9,411	0.364	0.4810	0	1
	Aboriginal or Torres Strait Is.	9,411	0.016	0.1252	0	1
	Father Ed Primary	9,411	0.112	0.3151	0	1
	Mother Ed Primary	9,411	0.086	0.2803	0	1
	Father Ed 10 Plus	9,411	0.459	0.4984	0	1
	Mother Ed 10 Plus	9,411	0.510	0.4999	0	1
	Father Occupational Status	9,411	48.156	23.521	0	100
	Mother Occupational Status	9,411	44.903	23.406	0	100
	Father Unemployed at Age 14	9,411	0.112	0.3152	0	1
	Mother Works at Age 14	9,411	0.715	0.4515	0	1
	Parents Broken Up at Age 14	9,411	0.141	0.3480	0	1
Cognitive	Backward Digit Span	9,411	5.135	1.4345	2	8
	Symbol Digit Modalities	9,411	53.372	10.474	9	99
Personality	Agreeableness	9,411	5.500	0.8497	2.25	7
	Conscientiousness	9,411	5.107	1.0090	1.1667	7
	Emotional Stability	9,411	5.055	1.0185	1.5	7
	Extraversion	9,411	4.478	1.1195	1.1667	7
	Openness to Experience	9,411	4.353	0.9840	1	7
Locus of Control	Can Do Anything - R	9,411	2.559	1.2486	1	7
	Cannot Change Things	9,411	2.390	1.2658	1	7
	Feel Pushed Around	9,411	2.461	1.3637	1	7
	No Way to Solve Problems	9,411	2.423	1.3198	1	7

Note: The table provides descriptive statistics for the full sample used in the analysis. All cognitive/non-cognitive variables are assumed to be cardinal for the calculations of means and standard deviations. Sample sizes, means, standard deviations, minimums and maximums are given.

Figure 2: Income Distributions - Annual and Five-Year Incomes



Note: The figure presents distributions of annual incomes (left panel) and five-year "permanent" incomes (right panel). Densities are depicted with histograms (greyscale) overlaid with with lognormal distributions $y \sim L\mathcal{N}\left(\mu;\sigma^2\right)$ with $\hat{\mu} = 10.915$ and $\hat{\sigma}^2 = 0.2383$, and $\hat{\mu} = 10.922$ and $\hat{\sigma}^2 = 0.2013$ respectively.

A2 Correlation Matrix - Cognitive/Non-Cognitive Variables

Psychological variables tend to have interesting covariance structures, which we present below. Standard Pearson correlations are given (which assume cardinality) although concordance measures which treat the variables as ordinal (i.e. Kendall τ estimates[23]) give similar results. Notably, our two intelligence measures are strongly positively correlated, as are the four measures of locus of control. Further, variables that tend to predict better economic outcomes (Judge *et al.*, 1999) are also positively associated, and hence the advantages associated with one cognitive or non-cognitive strength tend to be reinforced by others. Locus of control (negative scores on all four indicators) is correlated with both higher intelligence and greater levels of conscientiousness. Conscientiousness individuals also tend to be to be more agreeable, and have higher emotional stability scores, a trait that also exists for extroverted persons.

[23]Here $-1 \leq \tau \leq 1$ measures the discrepancy between concordant pairs and discordant pairs. A pair (x_1, y_1) is concordant with a second pair (x_2, y_2) if $x_1 > x_2$ and $y_1 > y_2$, or $x_1 < x_2$ and $y_1 < y_2$. A pair is discordant if the ranking switches. Adjustments can be made to normalize τ in the instance of ties.

Table 11: Correlation Coefficients - Cognitive/Non-Cognitive Skills

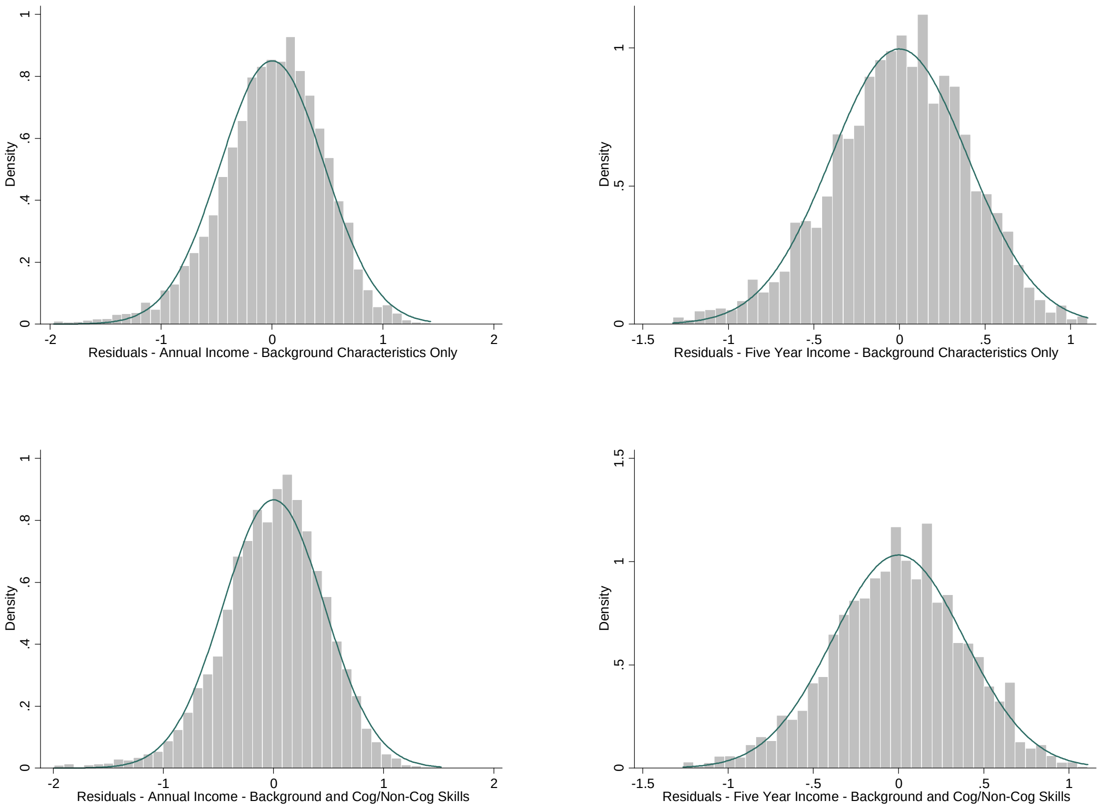
Type	Cog/Non-Cog	BDS	SDM	Agree	Conc	Stab	Extrv	Open	Can	Cont	Push	Solv
Intelligence	Back Digit Span	1.00										
	Symbol Digit Mod	0.34	1.00									
Big Five	Agreeable	0.03	-0.02	1.00								
	Conscientious	-0.02	0.09	0.18	1.00							
	Emotion Stable	-0.02	-0.03	0.14	0.28	1.00						
	Extroversion	0.01	0.02	0.18	0.08	0.18	1.00					
	Openness	0.12	0.03	0.26	-0.02	-0.19	0.01	1.00				
Loc of Cont	Can Do Anything	-0.02	-0.08	-0.15	-0.19	-0.17	-0.18	-0.06	1.00			
	Control Things	-0.06	-0.14	-0.12	-0.20	-0.22	-0.17	-0.02	0.37	1.00		
	Pushed Around	0.00	-0.08	-0.10	-0.25	-0.30	-0.22	0.08	0.36	0.63	1.00	
	Solve Problems	-0.02	-0.11	-0.12	-0.19	-0.27	-0.17	0.05	0.37	0.77	0.63	1.00

Note: The table presents correlation coefficients for the set of cognitive/non-cognitive skills. Bds - *Backward Digit Span*; Sdm - *Symbol Digit Modality Score*; Can - *Can Do Anything*; Cont - *Cannot Control Important Things in Life*; Push - *Feel Pushed Around*; Solv - *Cannot Solve Problems*; Agree - *Agreeableness*; Conc - *Conscientiousness*; Stab - *Emotional Stability*; Extr - *Extroversion*; Open - *Openness to Experience*.

A3 Distributional Plots - Conditional (Log)Normality

The Figures below present the residual distributions generated from EQ (5) for our two income variables. In all cases we can reject the null of normality, although this is largely driven by the large sample sizes. As shown, the departures from normality are small in all cases. Details on skewness/kurtosis are given in the table notes.

Figure 3: Appropriateness of Distributional Assumptions - Normal Fit for Log Income



Note: The panels show residual distributions for the models estimated in EQ (1) with a normal density superimposed in grey. While Jarque-Bera (Jarque and Bera, 1987) tests reject the null of normality in all cases, we observe that this is largely a function of the large sample size - departures from expected skewness and kurtosis scores are typically small. For the top left panel these values are {-0.57; 4.02} while for the top right panel we have {-0.29; 3.08}. The corresponding skewness/kurtosis values for the bottom panels are {-0.52; 4.05} and {-0.19; 2.97}. Thus our distributions are slightly negatively skewed and leptokurtic relative to our assumptions.