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ABSTRACT

Taller people earn more, especially in low- and middle-income countries. We present among the first evidence of this phenomenon in Africa, using longitudinal microdata on a cohort of middle-aged Kenyan adults. We document a substantial height/earnings premium: controlling for gender, age, and other socio-demographics, monthly earnings increase by 1.07% per centimeter (or 2.72% per inch). Nearly half this effect can be explained by differences in cognition, measured from an unusually rich battery containing 27 modules. Additional shares of the premium can be attributed to measures of physical strength and non-cognitive ability. In contrast to prior work, we find little role for occupational sorting: conditional on cognitive and non-cognitive ability, taller people do not appear more likely to work in higher paid sectors. Leveraging repeated measures of height and an instrumental variables specification, we find suggestive evidence that measurement error may be attenuating the estimated relationship.

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1 Introduction

Taller people have been shown to earn more, especially in low- and middle-income countries (LMICs). A host of papers have documented a positive relationship between physical stature and earnings, even after controlling for gender, age, and a vector of other socio-demographic characteristics (Thompson et al., 2023). A leading explanation is the correlation between height and cognitive ability. Nutrition and disease environment in childhood are strong predictors of adult height (Bozzoli et al., 2009; Jayachandran & Pande, 2017; Steckel & Prince, 2001)[1], and are also key inputs into cognitive development (Perkins et al., 2016). The height/earnings premium may thus be confounded with the labor market returns to cognition or educational attainment. In seminal work, Case and Paxson (2008) show that this is the case in samples of British and American adults, and they argue a large share of the height/earnings premium is mediated by measures of cognitive ability.

Despite this tenable hypothesis, most existing literature points to a residual height/earnings premium even after controlling for measures of educational attainment and cognitive ability. In a variety of settings, several papers show that additional shares of the premium can be attributed to non-cognitive abilities and occupational sorting: shorter people, even of similar cognitive abilities, disproportionately work in lower-paying sectors (Anderson, 2018; Lundborg et al., 2014; Vogl, 2014). A central challenge for this literature, however, is that available measures may proxy, but not fully capture, differences in cognition across individuals, leaving important questions unresolved. Does height predict earnings independent of cognition? And if so, what factors might explain the "residual" premium?

To shed further light on these questions, we leverage longitudinal microdata from the Kenya Life Panel Survey (KLPS), a unique dataset with anthropometric measures linked to a rich panel of respondent-level characteristics from childhood to middle-age. The KLPS was initiated in the late 1990s to track the long-term effects of childhood health and educational interventions[2] on the health, education, and economic outcomes of their recipients (Baird et al., 2016; Hamory et al., 2021; Kremer et al., 2009; Miguel & Kremer, 2004). The study has evolved into an unusual source of longitudinal data, with high respondent tracking rates and detailed measures of health, nutrition, fertility, earnings, and expenditures over the life course. The most recent fifth round of the KLPS (KLPS-5) collected both anthropometric measures and a detailed battery of 27 cognitive modules (based on the Harmonized Cognitive

[1] Numerous studies have also isolated this relationship either experimentally or quasi-experimentally. For work on sanitation, see Cameron et al. (2022) and Hammer and Spears (2016), and Bekele et al. (2020) for a systematic review. For work on nutrition, see Shrinivas et al. (2025) and Weaver et al. (2024).

[2] Namely, school-based deworming and girl's scholarship programs.

Assessment Protocol, HCAP; see Weir et al., 2016 and Gross et al., 2023), far beyond the cognitive measures available in most survey datasets in LMICs (or in rich countries in most cases). We leverage these data to document the height/earnings premium — and the contribution of cognition to explaining it — for the first time (to our knowledge) in an East African setting, and one of few times on the African continent more generally.[3]

First, we replicate prior work, documenting a substantial height/earnings premium in the KLPS sample. An extra centimeter (inch) of height is associated with a 1.07% (2.72%) increase in self-reported earnings, controlling for socio-demographic characteristics such as age, gender, religion, residential location, and ethnic group (tribe). This effect is substantial; moving one standard deviation up the height distribution for men increases earnings by 7.21%, over two thirds the naïve Mincerian return to a year of schooling in the KLPS sample.[4]

Next, we turn to the factors that may explain this relationship, exploiting the richness of KLPS. Adding to regressions a single cross-sectional Raven's score — a common cognitive performance measure used in existing literature (e.g. Vogl, 2014) — shrinks the estimated premium to 0.84%. However, this measure likely underestimates the contribution of cognitive ability to explaining the height premium. In a main finding, we show that replacing Raven's scores with five summary indices of cognitive ability across domains — constructed from 27 modules of survey questions assessing executive functioning, orientation, memory, visuospatial intelligence, and language fluency (Gross et al., 2025) — nearly doubles the share of the height premium that can be attributed to differences in cognition. In aggregate, controlling for these cognitive indices and respondent years of schooling shrinks the estimated height/earnings premium roughly in half to 0.55% per centimeter. These cognitive indices can explain 48.4% of the naïve height/earnings premium, estimated using standard socio-demographic controls. This compares to just 21.5% when using only a cross-sectional Raven's score. It is notable that, conditional on these controls, parental educational background explains little additional variation in earnings, and does not substantively change the estimate of the height/earnings premium.

Finally, we turn to measures of non-cognitive ability. Following a literature in rich countries on the labor market returns to personality (e.g. Flinn et al., 2025), we include in the regressions indices of the "Big 5" personality traits: extroversion, agreeableness, conscien-

[3]In their systematic review, Thompson et al. (2023) identify just one study with a singular focus on African countries: Schultz (2003), who focuses on Ghana and Cote d'Ivoire.

[4]In particular, regressing log earnings on years of schooling and respondent demographics yields an estimated semi-elasticity of 10%.

tiousness, negative emotionality, and open mindedness. These controls shrink the estimated semi-elasticity further to 0.49% per centimeter. Grip strength — a widely used proxy for respondents' physical strength — further shrinks the estimate to 0.38% per centimeter, and makes it statistically insignificant at conventional levels ($p = 0.203$). In contrast to prior work (Lundborg et al., 2014; Vogl, 2014), we find little role for occupational sorting beyond these controls: including a vector of granular occupational fixed effects raises the regression R^2 substantially, with only a small corresponding decrease in the estimated height/earnings premium. This suggests that differences in height across occupations can largely by explained by the correlation of height with measures of cognitive ability in this Kenyan setting.

These results aim to contribute to several lines of literature. A long literature in the empirical social sciences leverages average heights as measures of population well-being (Currie & Vogl, 2013; Steckel, 1995; Steckel & Prince, 2001). More narrowly, a large number of papers have sought to characterize the relationship between physical stature and labor market outcomes, leveraging augmented Mincerian wage regressions in the model of Case and Paxson (2008).[5] We attempt to build on this literature in several meaningful ways. First, Vogl (2014) highlights that a central challenge for work on height and earnings is that measurement of cognition — particularly in household surveys in low income settings — is often confined to a small set of measures capturing only some limited dimensions of respondents' cognitive ability. We relax these concerns using unusually detailed cognitive data, showing that relying on a single measure may greatly underestimate the contribution of cognition to explaining the height/earnings premium (Table 2).

Second, we shed new light on this question *geographically*, presenting the first evidence of the height premium in East Africa (a rapidly growing region with hundreds of million people), and some of the first evidence on the African continent more generally (Schultz, 2003). The results reinforce broad existing patterns in the literature, albeit with an estimated height premium considerably smaller than those presented in several other studies from other contexts (e.g. Bargain and Zeidan, 2017; Case and Paxson, 2008; Schick and Steckel, 2015; Vogl, 2014). These results are notable, especially given cross-country evidence that the link between per capita incomes and height in Sub-Saharan Africa may be weaker than elsewhere in the world (Deaton, 2007).

Finally, by leveraging panel data measures (which are unavailable in many other datasets) from prior rounds of KLPS, we are able to make progress in addressing several additional "open questions" in the literature on the height/earnings premium. For instance, the use of

[5] Examples include Bargain and Zeidan (2017), Bossavie et al. (2021), Case et al. (2009), LaFave and Thomas (2017), Lundborg et al. (2014), Schick and Steckel (2015), Sohn (2015), and Vogl (2014).

height observations taken at different points in respondents' adult lives allows us to evaluate the presence of measurement error-induced attenuation biases in the headline estimates, via an instrumental variables (IV) specification. This speaks to a concern raised in the existing literature (e.g. Case and Paxson, 2008) that may be especially relevant in LMICs, where anthropometrics are often taken during household surveys rather than in clinical settings, and hence are thought to be less precisely measured. We show that IV estimates are systematically higher than their OLS counterparts, though the degree of attenuation varies across specifications. Using measures of cognitive ability taken at multiple points in time, we are also able to address the potentially important role of changes in cognitive ability over the life course in explaining the height/earnings premium (see discussion in Vogl, 2014). We find little evidence to suggest that including measures of prior cognitive ability attenuates the estimated semi-elasticity.

2 Conceptual Framework

2.1 Set Up

To motivate the empirical analysis, we first consider a simple two period model of parental investment and child health in the spirit of Glewwe and Miguel (2007) and Vogl (2014). Consider a parent with a single child, endowed in the first period with time L. The parent must allocate their time between labor L_w, child-rearing L_c, and leisure L_l, such that $L = L_w + L_c + L_l$. The parent earns a wage w, determined exogenously, such that labor income in the first period is given by wL_w. In the second period, the parent does not earn wage income, but their child enters the labor market, earning income θ. The parent has two-period utility given by $U(c, L_l, \theta)$, where c denotes consumption in the first period. $U(\cdot)$ is strictly increasing in its inputs.

Children earn wages according to the following production function:

$$\theta = \theta(S, x, s^c, s^{nc}, o, \varepsilon) \tag{1}$$

where S denotes their years of schooling and x is a vector of exogenous socio-demographic characteristics. s^c and s^{nc} are their cognitive and non-cognitive skills, respectively, and ε is a structural residual. Finally, o represents the child's choice of occupation. We assume that θ is strictly increasing in S, s^c, and s^{nc}, and that the child selects o (via backwards induction) to maximize earnings.

The production functions for cognitive and non-cognitive skills are given as follows:

$$s^c = s^c(n, x, d, S, \varepsilon^c) \tag{2}$$

$$s^{nc} = s^{nc}(S, s^c, L_c, h, x, \varepsilon^{nc}) \tag{3}$$

where n denotes nutritional inputs in childhood, d is childhood disease background, and ε^c and ε^{nc} are the residuals. We model adult height as follows:

$$h = h(n, x, d, \varepsilon^h) \tag{4}$$

where $n, x,$ and d have the same definitions as above and again ε_h is a structural residual. These production functions are grounded in the empirical literature. Particularly in LMICs, adult height is at least partially determined by "net nutrition" in childhood, defined as the difference between nutritional inputs and nutritional demands, which include exposure to childhood diseases (Bozzoli et al., 2009; Perkins et al., 2016). Cognitive ability exhibits a similar production function, with nutrition and disease environment in childhood predicting cognitive development (Ip et al., 2017). In experimental work, both height and measures of cognition have been found to respond positively to interventions that improve nutrition (Carneiro et al., 2021; Ip et al., 2017; Weaver et al., 2024) or enhance sanitation (Cameron et al., 2022; Hammer & Spears, 2016), a proxy for disease environment. We model non-cognitive abilities as a function of schooling and cognitive ability, allowing a link between academic achievement and characteristics such as sociability, personality, and ambition. We further allow for the importance of demographic characteristics and parental investments in child-rearing.

Summarizing the above, the parent's optimization problem takes the following form:

$$\max_{L_l, L_w, L_c, c, n} U\left(c, L_l, \theta(S, x, s^c, s^{nc}, o)\right) \tag{5}$$

subject to:

$$L = L_w + L_c + L_l \tag{6}$$

$$wL_w = p_S S + p_n n + p_c c \tag{7}$$

where $p_S, p_n,$ and p_c are the exogenous prices of schooling, nutrition, and consumption, respectively, in period 1.

2.2 Results

This framework clarifies how the height/earnings premium emerges. Differentiating the earnings function with respect to height yields the following:

$$\left.\frac{\partial \theta}{\partial h}\right|_{o=o^*} = \underbrace{\left(\frac{\partial \theta}{\partial S} \cdot \frac{\partial S}{\partial h}\right)}_{\text{Schooling}} + \underbrace{\left(\frac{\partial \theta}{\partial s^c} \cdot \frac{\partial s^c}{\partial n} \cdot \frac{\partial n}{\partial h}\right)}_{\text{Cognitive } (+)} + \left.\underbrace{\left(\frac{\partial \theta}{\partial s^{nc}} \cdot \frac{\partial s^{nc}}{\partial h}\right)}_{\text{Non-cognitive}}\right|_{o=o^*} \tag{8}$$

where o^* denotes the optimal choice of occupation, solved via backward induction. This framework produces a key testable hypothesis, and points in the direction of an empirical strategy. First, within occupations, we expect a robust, positive relationship between earnings, cognition, and height. This follows the mechanism discussed at length by Case and Paxson (2008), as height and cognitive ability are co-produced from childhood nutritional inputs. We expect for taller people to also have higher cognitive abilities, and to in turn earn more in the labor market.

In contrast, this framework will be agnostic as to the contribution of schooling and non-cognitive abilities, independent of cognition. The derivative $\partial S/\partial h$ may be either positive or negative. Parents may trade off investments in schooling against investments in nutrition, or treat them as complementary, particularly if cognitive ability increases the marginal returns to schooling. Similarly, to the extent that parents trade-off time allocated to child-rearing against time allocated to wage labor, $\partial L_c/\partial h$ may take either sign. For the purposes of this paper, we leave these as empirical questions, foregoing imposing additional assumptions.

This framework also points in the direction of an empirical strategy. Equation 8 suggests that the height/earnings premium can be decomposed into components attributable to cognitive skills, non-cognitive abilities, and years of schooling. We will thus estimate linear models of the following form:

$$Y_i = \beta H_i + \gamma_1 S_i + \gamma_2 C_i + \gamma_3 N_i + \alpha' \mathbf{X}_i + \varepsilon_i \tag{9}$$

where Y_i denotes income, H_i, S_i, C_i, and N_i denote our measures of height, schooling, cognition, and non-cognitive abilities, respectively, and $\mathbf{X}_i$ is a vector of exogenous socio-demographic controls (i.e., age, gender and ethnicity).

In the framework above, children backward induct a choice o^* to maximize earnings θ. Holding occupation fixed, we can decompose the height/earnings premium into linear components attributable to cognition, non-cognitive abilities, and schooling. However, the potential for occupational sorting can induce non-linearities, making the empirical strategy less straightforward. Appendix Figure A1 presents simple diagrammatic intuition for this result. When the child has a choice between two occupations, each with distinct earnings functions $\theta(\cdot)$, realized earnings as a function of some input will trace the upper envelope of the earnings functions across both occupations. This suggests why existing work may find a role for occupational sorting (Lundborg et al., 2014; Vogl, 2014), even *after* controlling for measures of cognitive ability.

3 Data

3.1 Background

The KLPS is a longitudinal dataset, collecting detailed information on the lives of individuals who participated in one of two randomized human capital interventions as children: (i) the Primary School Deworming Program (PSDP), as discussed in Miguel and Kremer (2004) and the (ii) Girl's Scholarship Program (GSP), as discussed in Kremer et al. (2009). Both interventions were initiated in schools in Busia District (now Busia County), a rural region of Western Kenya, and KLPS respondents thus all resided there during baseline surveys. Since the roll-out, large shares of the KLPS sample have migrated outside of Busia and Western Kenya more generally, where they are tracked and surveyed in person by enumerators. Appendix Figure A2 summarizes these migrations systematically, mapping the spatial distribution of PSDP participants at baseline and during the KLPS Round 5 (KLPS-5) Cognitive-Plus (C+) Module, which forms the basis for most analysis in this study.

The KLPS is well-suited to investigating the height/earnings premium for several distinct reasons. First, KLPS is an unusually long panel dataset, collecting detailed information on 6,500+ respondents from 1998 to the present day. The KLPS-5 C+ module was collected during 2023-24, with past rounds — each often consisting of multiple visits to gather different modules — being collected approximately every 5 years. The panel structure is leveraged in several ways in this paper, including by allowing us to control for both contemporaneous and past measures of cognitive ability in earnings regressions (Appendix Table A3) and assess the presence of measurement error induced attenuation bias in estimated elasticities (Appendix Tables A1 and A2). Across all survey waves, over 86% of initial KLPS respondents have been surveyed at least once, and effective survey rates exceed 80% in each round, unusually high for longitudinal surveys of the KLPS's scale. Table 1 presents further detail on the sample analyzed in this study. At the time of KLPS-5 C+ data collection, respondents are on average 37 years of age, have 9.6 years of schooling, and have monthly earnings of 11274

KSh, approximately 90 USD.

The majority of the data analyzed in this study come from two survey modules within KLPS-5. The C+ Module included a detailed battery of cognitive assessments, and a series of questions about respondents' recent earnings and labor supply. The I+ Module collected detailed information on respondents' health, including anthropometrics such as height, weight, and grip strength, and a battery of psychometric measures used in this paper as measures of non-cognitive ability. In several cases, we also use measures collected in earlier rounds of the KLPS, particularly KLPS-3, administered between 2011 and 2014. For further detail, see the timeline presented in Appendix A.3.

3.2 Cognitive Ability

KLPS includes an unusually rich set of cognitive measures, based on the Harmonized Cognitive Assessment Protocol (HCAP), a cross-validated survey instrument commonly used to assess cognitive functioning among aging adults (Gross et al., 2023). The HCAP, as adapted for Kenya and used in this study, includes 27 distinct modules of cognitive survey questions, including measures of respondents' executive functioning, memory, language skills, orientation, and visuospatial functioning.[6] The richness of these measures allows us to advance certain aspects of the existing literature on the height/earnings premium, which generally focuses on a narrower set of measures of cognitive ability.[7] The KLPS sample is, to our knowledge, just one of a limited number of cohorts in Africa where the HCAP has been administered to date, making it a valuable source of information on the cognitive abilities of a cohort of middle-aged adults. Cognitive indices are constructed using Confirmatory Factor Analysis (CFA), a method commonly applied in the psychology literature to aggregate survey questions specific to individual domains into summary indices, and are designed to have mean zero and standard deviation one in the full KLPS sample. In the rest of this section, we provide further detail on some of the modules used to construct each of the domain-specific indices. For further detail, see Appendix B.1 and Gross et al. (2025).

Executive Functioning — The first domain of cognitive ability will be a score of executive functioning, the set of skills associated with goal-directed behaviors such as holding attention, remembering procedural steps, and multi-tasking. This measure is constructed

[6] Figure A6 presents pairwise correlations between these indices. The measures are strongly but imperfectly correlated, suggesting that they each convey new information on different dimensions of respondents' overall cognitive ability.

[7] Vogl (2014), who focuses on Raven's scores, for example, notes that "the Raven's matrix test measures just one dimension of cognitive skill; we would learn much from a richer set of cognitive tests."

from performance on several different sets of survey questions, including Raven's Progressive Matrix tests, where respondents view a series of visual patterns with missing pieces and are asked to select from a series of options which best fills in the blank. Several existing papers focus on Raven's matrices as measures of cognition; for example, Vogl (2014) example, uses them exclusively (as noted above), and LaFave and Thomas (2017) include them as the first of three measures of cognitive ability. Beyond Raven's tests, the index of executive functioning incorporates information from several other survey modules, including digit span tests, where respondents are asked to remember and repeat series of numbers, and "go-no-go" trials, where respondents are instructed to respond (or not respond) to a given stimulus by quickly pressing a button.

Memory — The second domain of cognition will be a memory score, administered in HCAP primarily to detect early signs of cognitive decline in aging adults. Memory is tested using a variety of vignettes and survey questions in which respondents are asked to remember details of a story, recall lists of words, or draw interlocking shapes they are presented with after short lags. These survey questions extend significantly on those used to assess working memory in other research on the height/earnings premium; LaFave and Thomas (2017), for example, focus exclusively on a ten-word recall exercise.

Visuospatial — The third domain of cognition is an index of visuospatial ability, assessing respondents' ability to process and retain visual information. The score is constructed from three sets of survey questions, where respondents are asked to (i) copy images of interlocking pentagons, (ii) draw clocks, and (iii) draw (both immediately and with delay) a series of geometric shapes, such as pyramids, cubes, and overlapping circles. To the best of our knowledge, few existing studies of the height/earnings premium consider measures of visuospatial intelligence.[8]

Orientation — The fourth domain of cognitive ability is an orientation score, aimed at capturing the respondent's awareness of their circumstances, including time and place. The primary module for assessing orientation is the Swahili Mental State Exam, in which respondents are asked questions including to name the day, month, season, and year, their country and city of residence, and the current Kenyan or Ugandan president (see Gross et al., 2025 for more details). These questions are used primarily to assess cognitive decline in older adults, and therefore they produce consistently high scores and relatively little variation in the KLPS sample (Gross et al., 2025). Given this, we expected *a priori* for this index to be a weak predictor of earnings, a hypothesis confirmed by the data (see Table 2 for details).

[8]One exception is Böckerman et al. (2017), who focus on them almost exclusively.

Language/Fluency — The fifth domain is a measure of language fluency, assessing respondents' capacity to communicate in Swahili, one of two national languages in Kenya (the other is English) and the language in which the KLPS is administered. Questions used to construct this index ask respondents to name common objects (e.g. scissors or watermelons) from pictures, name as many animals as possible in a given time frame, follow basic verbal instructions, or explain how to travel to the nearest market. The types of questions employed are standard across HCAP surveys, but were adapted where necessary to the local context.

3.3 Non-Cognitive Abilities

Prior literature on the height/earnings premium has also pointed to the importance of non-cognitive skills (Lundborg et al., 2014). Therefore, we supplement these measures of cognitive ability with several dimensions of non-cognitive ability.

Big 5 Personality Measures — The first set of measures of non-cognitive ability will be indices constructed based around the "Big 5" personality measures, namely, agreeableness, extroversion, conscientiousness, negative emotionality, and open mindedness. Use of the measures follows a literature in labor economics, primarily in rich countries, documenting the labor market returns to individual personality traits (e.g. Flinn et al., 2025). Indices are constructed using the Extra Short Form Big 5 Inventory (BFI-2-XS) developed and validated by Soto and John (2017). Survey questions ask respondents to state their degree of agreement (on a scale of 1 to 5) with a statement about themselves, such as "tends to be quiet" or "is sometimes rude to others." These numeric codes are summed across questions for each personality trait, and then standardized in the analysis sample to have mean zero and standard deviation one.[9]

Importantly, the validity of these measures in non-Western populations is the subject of debate (Laajaj et al., 2019; Schmitt et al., 2007). Laajaj and Macours (2021), for example, document substantial non-classical measurement error in personality measures in a different sample in Western Kenya. We replicate several of their diagnostics using the KLPS data, documenting similarly low pairwise item correlations (Appendix Figure A7). Since these measures are not the primary focus of this study, we include them in regressions regardless. However, we caution that they may not be ideal proxies of the underlying personality constructs, making interpretation more difficult.

Grip Strength — Beyond personality, we also consider grip strength, a measure that has been used by several other studies of the height premium as a measure of physical strength

[9] For further detail on survey questions and the construction of the index, see Appendix B.2

(Lundborg et al., 2014; Sohn, 2015). Grip strength is assessed during household surveys using a portable handheld dynamometer, and is measured (in kilograms) twice in short succession. Measures reported in this paper are averaged over these two attempts.

3.4 Earnings

Earnings are reported for three primary classes of activity: (i) agriculture, (ii) self-employment, and (iii) formal employment. Earnings from self-employment and formal employment are reported by respondents for the previous 30 days, and agricultural earnings are reported from the previous twelve months. The primary measure of total earnings will be the sum of earnings from self-employment and formal employment, plus earnings from agriculture divided by twelve.[10] The distribution of earnings in the KLPS-5 C+ data is substantially right-skewed, as expected (see Appendix Figure A5); therefore, we restrict to the subset of respondents with non-missing reported earnings and take a natural log transformation (following Vogl, 2014).

3.5 Other Measures

Height — Height is measured in the KLPS-5 I-Module by enumerators using a tape measure twice in short succession. Heights analyzed in this paper are the average of these two attempts.[11] One concern raised in prior literature on the height/earnings premium is measurement error (Case & Paxson, 2008). Classical measurement error in earnings (as the dependent variable) will yield noisier coefficients; however, measurement error in height (an explanatory variable) may cause attenuation biases, underestimating the semi-elasticity of interest. These concerns may be especially relevant in low and middle-income country settings, where anthropometrics are often measured during surveys in the home (as is the case in KLPS), rather than in a clinical setting.

The longitudinal nature of the KLPS data is useful for addressing these concerns. The primary height measurements leveraged in this study are drawn from KLPS-5; however, heights were also measured for respondents in KLPS-3, approximately ten years prior but after the point at which respondents would be expected to achieve their full adult height

[10] We focus on monthly rather than hourly earnings to adhere to the recall periods of survey questions; however, all results presented are qualitatively similar when controlling for self-reported work hours in the previous month. See Appendix Tables A6 and A7 for detail.

[11] We exclude four extreme negative outliers where height is recorded as less than 110 centimeters; these are almost assuredly the result of unintentional misreporting by enumerators.

(i.e. respondents were already mainly in their 20s). This allows us to assess the correlation between two distinct measures of height, taken ten years apart but under similar field conditions. In addition, it allows us to leverage one measure of height as an instrument for the other, purging the estimated semi-elasticity of classical measurement error, following the approach of Ashenfelter and Krueger (1994). We find mixed evidence of attenuation bias across different specifications; however, since relying on earlier height measurements shrinks the sample size considerably, we focus on OLS estimates in the main body of this paper.

Demographics — Outside of these measures, we include a variety of fixed effects, including for respondents' gender, religion, location, tribe,[12] and whether their mother and father attended secondary school. Unlike some prior work, which excludes women on the basis of endogenous labor force participation (e.g. Vogl, 2014), we include female respondents and control for level differences in earnings with a gender fixed effect.[13] This is primarily because labor force participation is common among women in the KLPS sample, echoing high rates of labor participation in Kenya as a whole (Byambaa et al., 2025): 44.8% report earning some money from self-employment in the previous 30 days, and 34.6% report earning wages from formal employment. Furthermore, it is notable that point estimates are consistent with a *larger* height premium for women than men (Appendix Table A4). To reduce dimensionality in terms of religious identity, we collapse all Protestant Christian groups occupying less than 5% of the sample into a single category.[14] Location fixed effects almost always correspond to the county; however, in cases where cells are sparse, we combine neighboring counties.

4 Results

4.1 Graphical Evidence

Figure 1 presents graphical evidence on the relationship between height, earnings, and different measures of human capital in the KLPS sample. Curves correspond to local polynomial

[12]The vast majority of the KLPS sample is of Luhya origin. Therefore, we include fixed effects for respondent's subtribe, namely, Luhya-Samia, Luhya-Nyala, Luhya-Khayo, Luhya-Marachi, or other Luhya ancestry. Other ethnic groups represented with fixed effects include Luo and Teso. An additional indicator is used for the small number of respondents for whom ethnicity is missing.

[13]Appendix Tables A4 and A5 explore heterogeneity in the height/earnings premium within genders. We deprioritize this heterogeneity in the main analysis, owing to limited statistical power on the interaction term. For more detail on the factors contributing to the level difference in earnings between men and women in the KLPS sample, see Byambaa et al. (2025).

[14]Examples of the groups so collapsed include Baptists, Jehovah's Witnesses, Seventh Day Adventists, and Roho Christians. Religious groups identified with unique indicators include Catholics, Anglicans, Pentecostal Christians, Gospel/New Testament/Injili Christians, Muslims, and those with no stated religion.

regressions, fit to the data for men and women, respectively. The first panel plots the primary relationship of interest, the semi-elasticity of earnings with respect to height for women and men, respectively. Independent of any controls, we observe a robust, positive association between height and logged earnings. The second panel presents the relationship between height and an index of executive functioning. Consistent with the predictions of the conceptual framework and Case and Paxson (2008), we observe a positive relationship between height and this measure of cognitive ability. The bottom panel replicates this exercise for the measure of grip strength, which exhibits a high degree of correlation with height. These figures confirm the existence of a height/earnings premium for both men and women in the KLPS sample, and suggest several candidate confounding variables that may help explain this relationship.

4.2 Estimation

To estimate the height/earnings premium more rigorously, we now turn to regression analysis. The main estimating equation takes the following form:

$$\ln Y_i = \beta H_i + \tau S_i + \alpha' \mathbf{C}_i + \theta' \mathbf{N}_i + \gamma' \mathbf{X}_i + \varepsilon_i \tag{10}$$

where $\ln Y_i$ denotes self-reported logged monthly total earnings[15] for individual i and H_i is a continuous measure for respondent i's height, measured in centimeters.[16] $\hat{\beta}$ is the estimated height/earnings premium, defined as the percent increase in earnings associated with a one centimeter increase in height. S_i denotes years of schooling, and $\mathbf{C}_i$ and $\mathbf{N}_i$ are vectors of cognitive and non-cognitive skills, respectively. Finally, $\mathbf{X}_i$ represents a vector of additional respondent-level characteristics, including gender, tribe, location, religion, and age.

[15] Though several studies have chosen to model the relationship between logged earnings and logged height (e.g. LaFave and Thomas, 2017), we follow Case and Paxson (2008) and focus on the semi-elasticity of earnings with respect to height in levels. Appendix Figure A4 presents diagnostics underpinning this choice; the distribution of heights within genders is approximately normal, with no obvious skew.

[16] In ancillary specifications, we consider a version of this model where $\ln Y_i = \beta_1 H_i + \beta_2 F_i + \beta_3 H_i F_i + \gamma' \mathbf{X}_i + \varepsilon_i$, where F_i is an indicator denoting the respondent is female. In this specification, the estimates of the height/earnings premium will be $\hat{\beta}_1$ and $\left(\hat{\beta}_1 + \hat{\beta}_3\right)$ for men and women, respectively. We de-prioritize these results in the main analysis, as limited power implies we cannot reject sizable differences in the height premium across subgroups. See Appendix Tables A4 and A5 for detail.

4.3 What Explains the Height Premium? The Role of Cognition

We begin by estimating a simple regression of log earnings on height, controlling for only gender, religion, tribe, age, and location. Column (1) presents the estimated semi-elasticity: an increase in height of one centimeter (inch) is associated with a 1.07% (2.72%) increase in earnings. This effect is substantial; moving one standard deviation up the height distribution for men (6.73 centimeters) is associated with a 7.21% increase in monthly earnings. This is over two thirds the naive return to a year of schooling in the KLPS sample. The R^2 of this basic specification is 0.25, suggesting height and demographics alone explain a substantial share of the variation in earnings across KLPS respondents.

Columns (2) through (6) supplement this base specification with measures of cognitive ability, described in detail above. In line with other work (Bossavie et al., 2021; Case & Paxson, 2008; LaFave & Thomas, 2017; Vogl, 2014), we find that differences in cognitive ability explain substantial shares of the height/earnings premium. Column (2) adds to the regression a single, cross-sectional Raven's score, one of many measures of executive functioning available in the KLPS and one that has been used in other work as the sole measure of cognition (e.g. Vogl, 2014). The semi-elasticity of earnings with respect to height declines by roughly a quarter from 1.07% to 0.84%, suggesting a substantial role for that aspect of cognition in mediating the relationship between earnings and height.

As discussed in Section 3, a key benefit of using KLPS data is the richness of its cognitive measurement. Raven's Progressive Matrices tests constitute just one of 27 cognitive tests administered to KLPS respondents, allowing us to assess the contribution of other dimensions of cognitive ability to explaining the height/earnings premium. Column (3) of Table 2 replaces the cross-sectional Raven's score with an index of executive functioning, constructed from both Raven's scores and a number of other cognitive modules measuring attention, focus, problem solving, reasoning, and working memory. Adding this index shrinks the estimated semi-elasticity to 0.65%, substantially below that estimated with the single cross-sectional Raven's score.

Including an index of orientation does little to the headline coefficient, but including an index of memory shrinks it further to 0.61%. Visuospatial skills explain essentially no additional variation; including an index of them in the regression does not substantively change either the estimated semi-elasticity or R^2, and the coefficient on the index is negative in sign and not statistically significant. Column (7) presents estimates when including the full set of five cognitive domain indices, which bring the estimated semi-elasticity to 0.6%. In aggregate, the cognitive indices can explain 43.9% of the naive height premium estimated in Column (1), compared to 21.5% when using only the cross-sectional Raven's score. This suggests that more detailed measurement may be necessary to more fully characterize the contributions of cognitive ability to explaining the height/earnings premium.[17]

Column (8) presents the richest version of the base specification, adding to Column (7) a control for respondents' years of schooling. Conditional on educational attainment, other cognitive controls, and demographics, the index of executive functioning remains a strong predictor of earnings, with a one standard deviation increase associated with a 26.7% increase in earnings. We also find strong evidence of an association between earnings and the index of language fluency. In contrast, we find no evidence of labor market returns to the index of visuospatial intelligence, and smaller effects of the indices of memory and orientation. In total, these variables explain 48.4% of the height/earnings premium estimated in Column (1), confirming the view that cognitive ability and educational attainment mediate a large share of the relationship between height and earnings in this Kenyan setting.

4.4 Childhood Background, Non-Cognitive Abilities and Occupational Sorting

Next, we turn to non-cognitive measures, including family background, personality, and occupational choice. As formalized in Section 2, one important hypothesis for the height/earnings premium is the co-production of both height and human capital through nutrition, disease environment, and economic circumstances more generally in early childhood. Therefore, we might expect for measures of childhood socioeconomic status to explain part of the residual height/earnings premium unexplained by the measures of cognition. To test this hypothesis formally, we supplement the earlier regressions with indicators for whether a respondent's mother and father, respectively, attended secondary school. The estimated coefficients on both indicators are positive and statistically significant, as hypothesized, but do little to change the headline semi-elasticity.

Following from a literature in labor economics estimating the labor market returns to personality, we next turn to survey-based indices, capturing the widely used "Big-5" personality traits. Work in rich countries has found that these indices are strong predictors of earnings (Flinn et al., 2025). Including these proxies for the "Big 5" personality traits shrinks the headline semi-elasticity slightly, from 0.54% to 0.49%. In addition, we see that even conditional on a rich vector of cognitive and demographic controls, personality traits predict

[17] In contrast, we find no evidence to suggest that measures of prior cognition (measured in earlier KLPS rounds) explain addition variation beyond these included controls. See Appendix Table A3 for detail.

earnings. For example, logged earnings are increasing in the index of conscientiousness and decreasing in the index of agreeableness. The signs of these coefficients coincide with those reported in Flinn et al. (2025), who estimates the labor market returns to personality using German panel data.

In Column (4), we add a measure of grip strength. In many LMICs, large shares of the workforce are employed in physically demanding occupations such as agriculture, fishing, or construction. In the KLPS sample analyzed in this study, for example, 82.5% of respondents agree or strongly agree that their job is "physically demanding". To the extent that height and physical strength are positively correlated (see Figure 1), this suggests that strength may play a role in mediating the height/earnings premium. The results suggest this may be the case: adding grip strength to the regression shrinks the estimated semi-elasticity from 0.49% to 0.38% per centimeter. In this specification, the estimated height/earnings premium is no longer statistically significant at conventional significance levels ($p = 0.203$).

Previous studies in other contexts have documented a substantial role for occupational sorting in explaining the height premium (Lundborg et al., 2014; Vogl, 2014). To investigate this hypothesis, we add to the regressions a vector of occupational fixed effects, indicators for whether a respondent's primary occupation falls into one of 48 categories. Including these fixed effects raises the explanatory power of the model substantially, increasing the R^2 from 0.32 to 0.46. However, in contrast to prior work (Lundborg et al., 2014; Vogl, 2014), they leave the estimated semi-elasticity essentially unchanged, shrinking it from 0.38% to just 0.35% per centimeter. This is despite the fact that, before controls, the distribution of heights differs substantially across occupations (Appendix Figure A8). This suggests that cognitive and non-cognitive abilities play a key role in facilitating occupational sorting.

As discussed above, a key advantage of the KLPS data is the ability to purge the estimated height/earnings premium of measurement error by leveraging repeated height measurements as instruments for one another. Doing so requires dropping some observations for whom KLPS-3 height data is missing; therefore, we re-estimate the models above on this subset of respondents both with OLS and IV to facilitate comparability across samples. Results from this exercise are presented in Appendix Tables A1 and A2. Consistent with the predictions of econometric theory, IV estimates exceed their OLS counterparts by between 2 to 86%, depending on specification. This result is striking, especially given that any measurement error in height appears relatively mild (e.g. the correlation between KLPS-3 and KLPS-5 heights is 0.90). Though we cannot formally reject the equivalence of IV and OLS coefficients, and thus do not emphasize the IV results, these patterns nonetheless suggest that measurement error may be attenuating headline coefficients in other work on the height/earnings premium.

Figure 2 situates these results within the wider literature, comparing the estimated height/earnings premium in this paper to those in several other papers using datasets from other countries. Our estimate of the height/earnings premium is smaller than those reported in several other datasets, including the 1958 U.S. National Childhood Development Study (Schick & Steckel, 2015), 1970 British Cohort Study (Case & Paxson, 2008), Mexican Family Life Survey (Vogl, 2014), and Indonesia Family Life Survey (Bargain & Zeidan, 2017). This result is notable, given work by Deaton (2007) suggesting that in cross-country data, the link between per capita incomes and average heights in Sub-Saharan Africa may be weaker than other regions of the world.

5 Conclusion

In this paper, we revisit the height/earnings premium, using rich longitudinal microdata on a cohort of Kenyan adults. We document a substantial naïve height/earnings premium, and leverage unusually rich measurement of cognitive and non-cognitive skills to evaluate the factors that contribute to its emergence. We find that indices of cognitive ability can explain nearly half of the naïve premium, and that the full set of variables — inclusive of personality traits, parental educational background, grip strength, and occupational fixed effects — shrink it by roughly two thirds. Unlike in other work (Bargain & Zeidan, 2017; Vogl, 2014), the estimated "residual" premium is small in magnitude and not statistically significant at conventional levels. We further present evidence that measurement error in height may be biasing estimated semi-elasticities downward substantially, suggesting that future work on the height/earnings premium should consider measurement issues carefully when interpreting magnitudes of effects.

This is, to the best of our knowledge, among the first studies to revisit the height premium using Sub-Saharan Africa data. The results reinforce patterns documented elsewhere, despite debate as to whether the gradient between heights and socioeconomic circumstance are weaker in Africa than elsewhere in the world (Deaton, 2007). More speculatively, the finding that the rich set of KLPS cognitive measures allow us to explain substantially more of the height/earnings premium than less detailed measures suggests that other studies may be underestimating the importance of cognition as a mediator.

Importantly, these results do not address several remaining puzzles for this literature. The fact that cognition mediates the height/earnings premium, for example, tells us little about whether such relationships emerge as a result of statistical discrimination, endogenous sorting, or differences in performance while on the job. The limits of the data further do not us allow us to reject substantial residual height premia, or to explain the differences between women and men with much confidence. These remain useful directions for future research.

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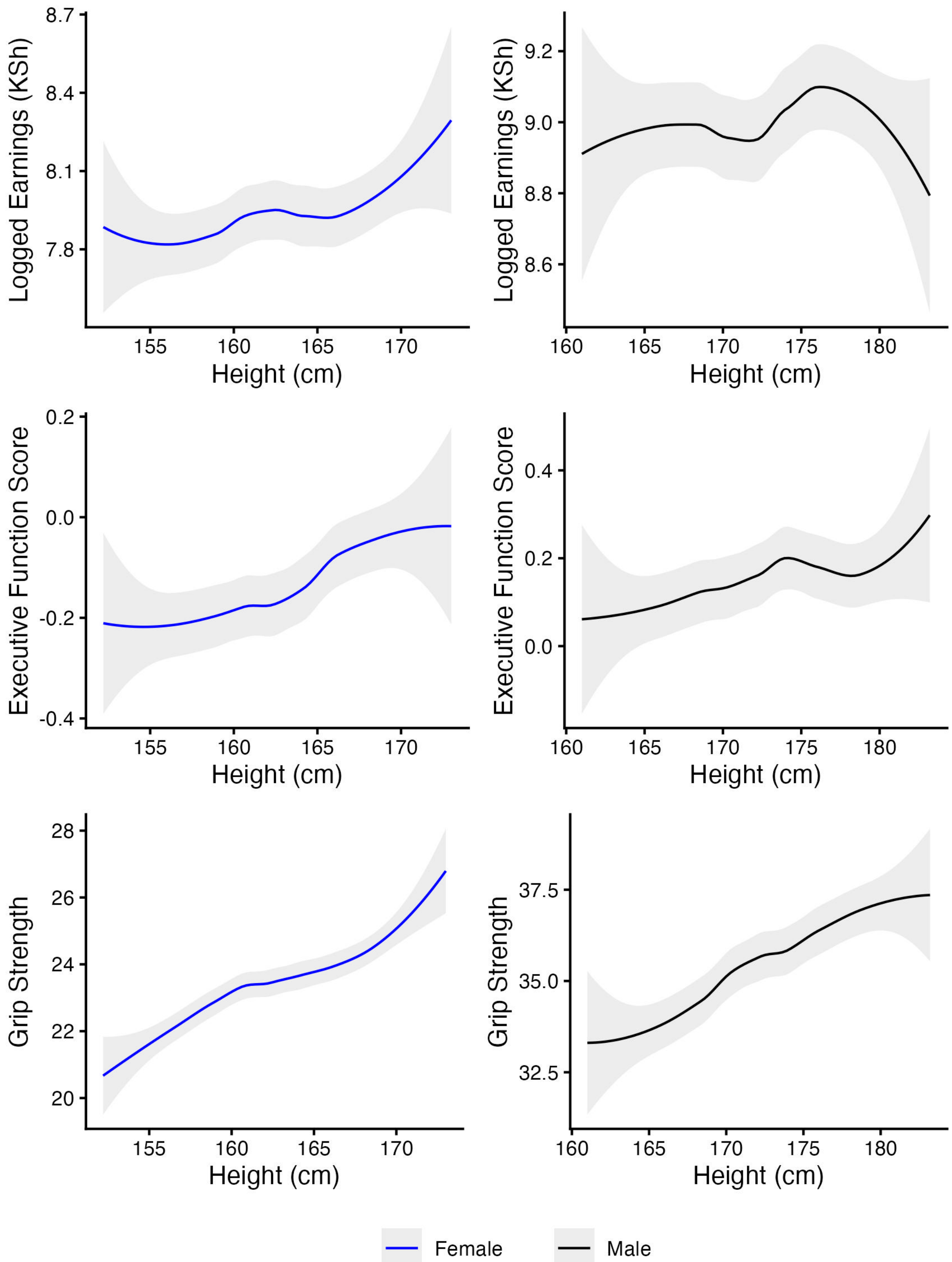
6 Main Exhibits

Table 1: Descriptive Statistics

Variable	Mean	SD	10th	90th
Socio-Demographics				
Age	37.01	2.6	34	41
Female	0.55	0.5	0	1
Rural	0.6	0.49	0	1
Employment				
Primary Occupation: Farming/Fishing	0.34	0.47	0	1
Primary Occupation: Retail/Commercial	0.19	0.4	0	1
Primary Occupation: Unskilled Trades	0.12	0.33	0	1
Primary Occupation: Skilled Trades	0.09	0.28	0	0
Primary Occupation: Professional	0.11	0.31	0	1
Monthly Hours Worked	178.94	120.46	25.74	335
Anthropometrics				
Height (cm)	166.92	8.06	157	177.6
Weight (kg)	69.24	13.12	54	86.49
Grip Strength (kg)	28.82	9.05	18.25	41.1
Childhood Background				
Years of Schooling	9.65	2.97	6	13
Father Has Any Secondary Schooling	0.41	0.49	0	1
Mother Has Any Secondary Schooling	0.18	0.38	0	1
Earnings				
Total Monthly Earnings (KSh)	12100.07	25802.34	500	29979.17
Monthly Earnings from Agriculture (KSh)	825.82	2413.78	0	2000
Monthly Earnings from Wages (KSh)	7117.74	17715.44	0	21000
Monthly Earnings from Self-Employment (KSh)	4156.51	17446.63	0	10000

N = 4576. This table presents descriptive statistics on the KLPS sample analyzed in this paper. Variables are drawn from the KLPS-5 C+ and I+ Modules. The sample is slightly female skewed because participants in the GSP intervention were exclusively female.

Figure 1: Height, Earnings, and Human Capital



N =4128. This figure plots the relationship between height and several variables of interest in the analysis sample. Respondents with heights below the 5th or above the 95th percentile of height within genders are excluded, due to limited mass in the tails of the distribution. Lines are local polynomial regressions with tricube kernel weights. Gray bands are point-wise 95% confidence intervals.

Table 2: Cognition and the Height/Earnings Premium

	Logged Earnings							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Height (cm)	0.0107***	0.0084***	0.0065**	0.0065**	0.0061**	0.0061**	0.0060**	0.0055*
	(0.0031)	(0.0031)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
Raven's Score (KLPS-5)		0.2406***						
		(0.0218)						
Executive Functioning			0.4351***	0.4129***	0.3440***	0.3501***	0.3059***	0.2656***
			(0.0260)	(0.0266)	(0.0299)	(0.0317)	(0.0326)	(0.0332)
Orientation				0.1006**	0.0776*	0.0788**	0.0618	0.0660
				(0.0399)	(0.0401)	(0.0401)	(0.0403)	(0.0405)
Memory					0.1160***	0.1177***	0.0834***	0.0680**
					(0.0256)	(0.0258)	(0.0269)	(0.0268)
Visuospatial						−0.0191	−0.0289	−0.0574*
						(0.0335)	(0.0337)	(0.0340)
Language Fluency							0.1555***	0.1285***
							(0.0357)	(0.0355)
Years of Schooling								0.0571***
								(0.0079)
Respondent Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FEs	No	No	No	No	No	No	No	No
Observations	4,576	4,576	4,576	4,576	4,576	4,576	4,576	4,576
Adjusted R^2	0.246	0.266	0.295	0.296	0.299	0.298	0.301	0.310

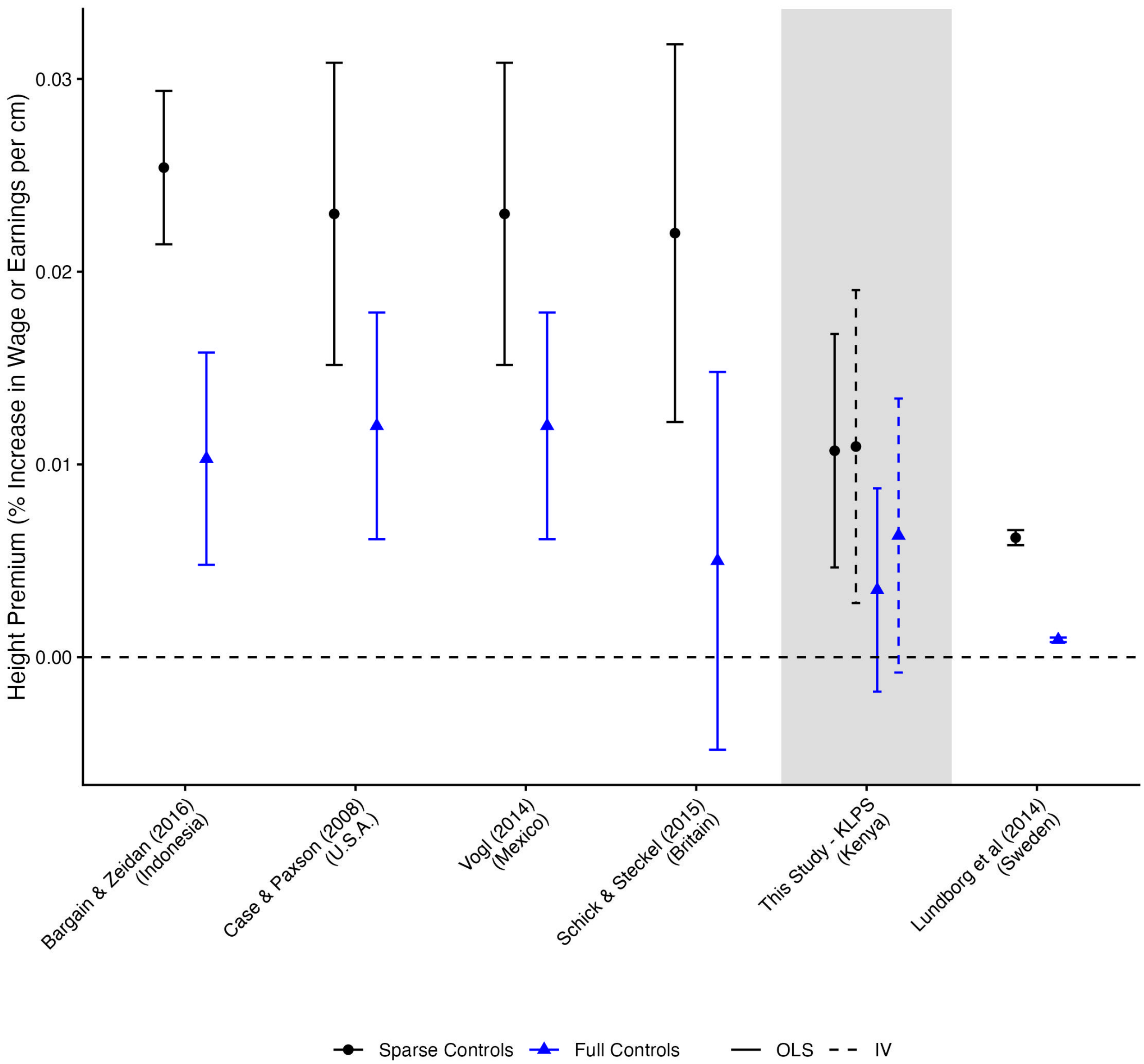
The outcome is logged earnings in the previous 30 days, summing across agriculture and income from wages and businesses. Cognitive indices are standardized to have mean zero and standard deviation one. Respondent demographics include gender, religion, age, tribe, and location. Robust standard errors in parentheses. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

Table 3: Childhood Background and Non-Cognitive Abilities

	Logged Earnings				
	(1)	(2)	(3)	(4)	(5)
Height (cm)	0.0055*	0.0054*	0.0049*	0.0038	0.0035
	(0.0030)	(0.0030)	(0.0029)	(0.0030)	(0.0027)
Secondary Education: Father		0.1005**	0.0963**	0.0968**	0.0487
		(0.0418)	(0.0416)	(0.0416)	(0.0374)
Secondary Education: Mother		0.1331**	0.1204**	0.1231**	0.0439
		(0.0533)	(0.0530)	(0.0531)	(0.0480)
Extroversion			0.1267***	0.1236***	0.1017***
			(0.0257)	(0.0258)	(0.0228)
Agreeableness			−0.1099***	−0.1116***	−0.0826***
			(0.0347)	(0.0348)	(0.0314)
Conscientiousness			0.1216***	0.1195***	0.1017***
			(0.0335)	(0.0335)	(0.0296)
Negative Emotionality			−0.0167	−0.0164	−0.0148
			(0.0238)	(0.0238)	(0.0210)
Open Mindedness			0.0620**	0.0589**	0.0429*
			(0.0284)	(0.0285)	(0.0251)
Grip Strength				0.0052*	0.0046*
				(0.0030)	(0.0027)
Respondent Demographics	Yes	Yes	Yes	Yes	Yes
Cognitive Controls	Yes	Yes	Yes	Yes	Yes
Occupation FEs	No	No	No	No	Yes
Observations	4,576	4,576	4,576	4,576	4,576
Adjusted R^2	0.310	0.312	0.321	0.321	0.463

The outcome is logged earnings in the previous 30 days, summing across agriculture and income from wages and businesses. All regressions include variables for cognitive controls, as in Table 2. Non-cognitive measures are discrete indices taking values 0-15, standardized in the analysis sample to have mean zero and standard deviation one. Occupation fixed effects include indicators for 48 distinct primary occupations. Respondent demographics include gender, religion, age, tribe, and location. Robust standard errors in parentheses. $^{*}p < .10,^{**}p < .05,^{***}p < .01$.

Figure 2: The Height/Earnings Premium in Comparative Perspective

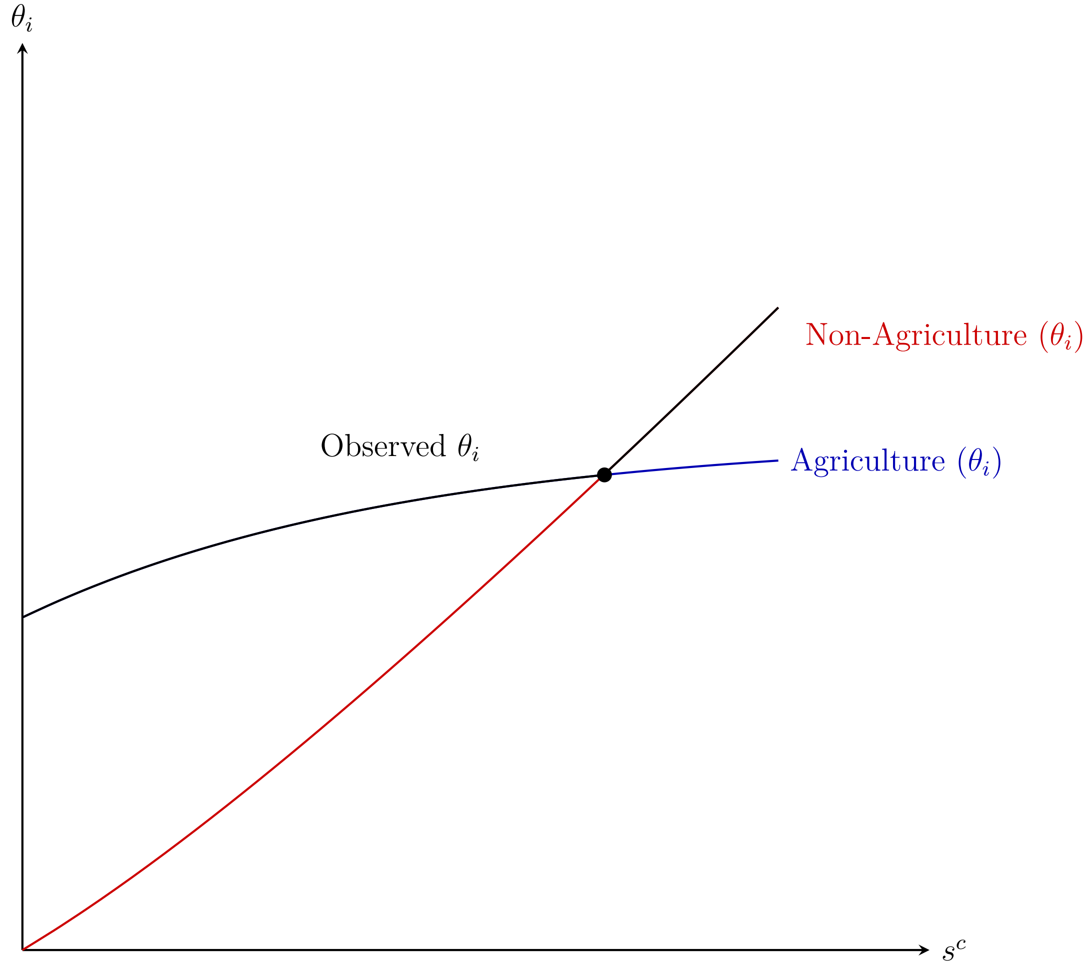


This figure plots the height/earnings premium as reported in this study against those estimated in several other studies from different geographic contexts. All coefficients reported are semi-elasticities, and all confidence intervals are at the 95% level. "Sparse controls" corresponds to reported estimates of the height/earnings premium in each paper's sparsest model. The exact controls included varies slightly across papers; e.g. Case and Paxson (2008) include only ethnicity, while Bargain and Zeidan (2017) include age, ethnicity, and province of residence. "Full controls" correspond to each papers' richest specification, i.e. the model described by the authors as explaining the largest share of the height/earnings premium. The four estimates presented for this study (from left to right) correspond to Column (1) of Table 2, Column (1) of Table A1 (Panel B), Column (5) of Table 3, and Column (5) of Table A2 (Panel B).

A Additional Exhibits

A.1 Conceptual Framework

Figure A1: Cognitive Ability and Occupational Sorting



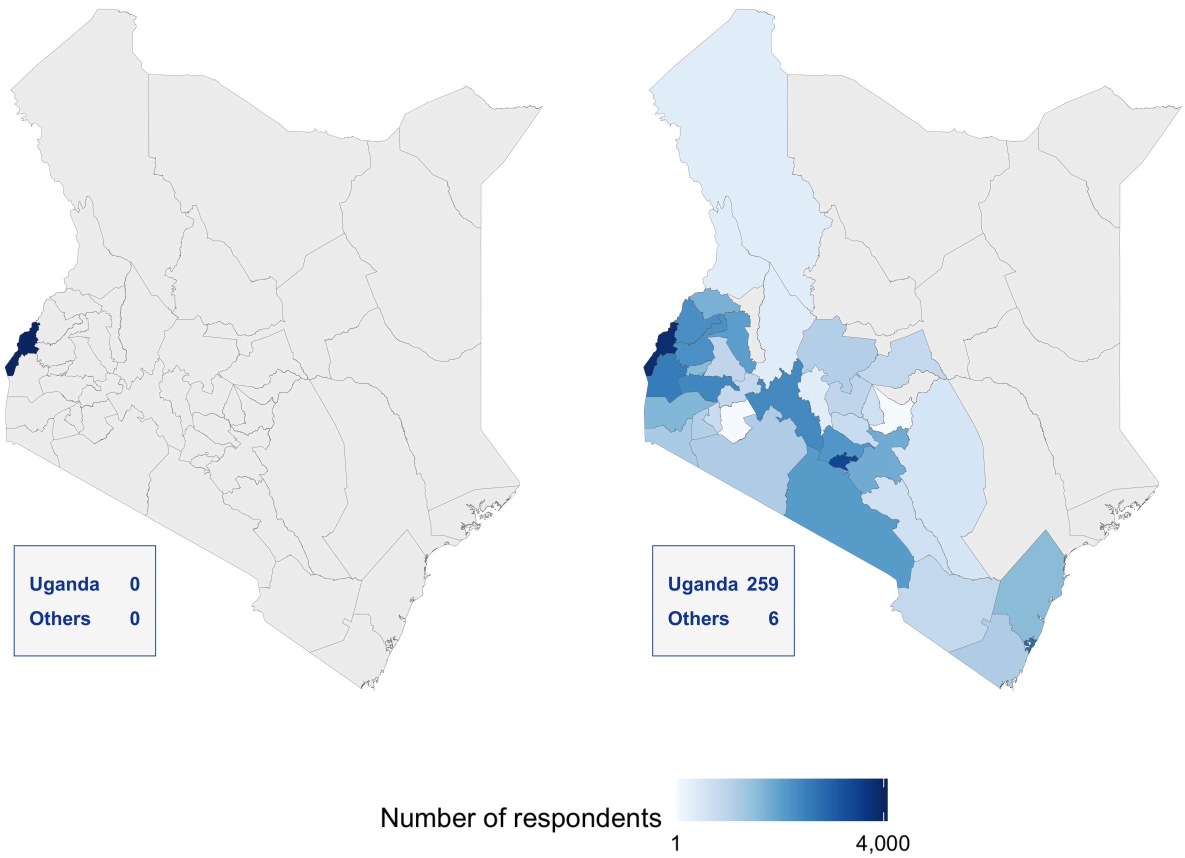
This figure presents diagrammatic intuition for non-nonlinearities in the link between cognition and earnings that can be induced by occupational sorting. For further detail, see the conceptual framework in Section 2.

A.2 Geographic Distribution of PSDP Respondents

Figure A2: Geographic Distribution of KLPS Respondents Over Time

(a) PSDP Baseline Survey

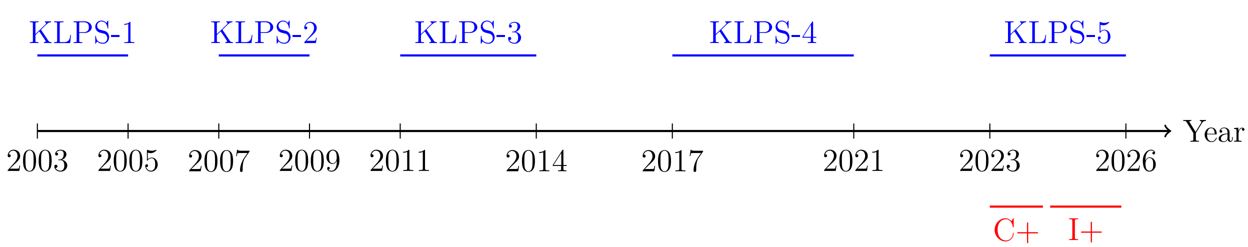
(b) KLPS-5



Note: These maps plot the geographic distribution of the full KLPS cohort across Kenyan counties during the PSDP baseline ($N = 7,500$) and the KLPS-5 C+ Module ($N = 5,380$), respectively.

A.3 KLPS Timeline

Figure A3: Timeline of Key KLPS Activities



A.4 Descriptive Statistics

Figure A4: Distribution of Height by Gender (KLPS-5)

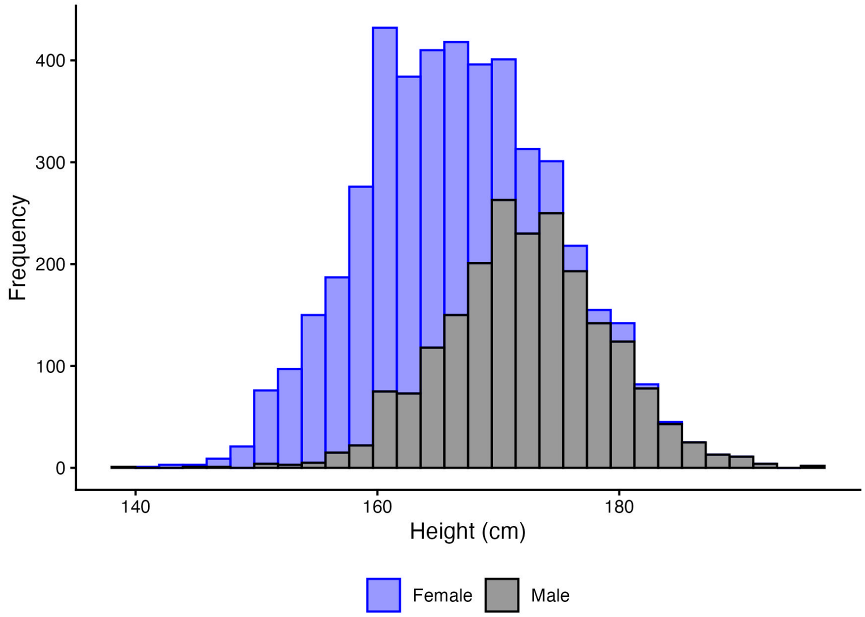
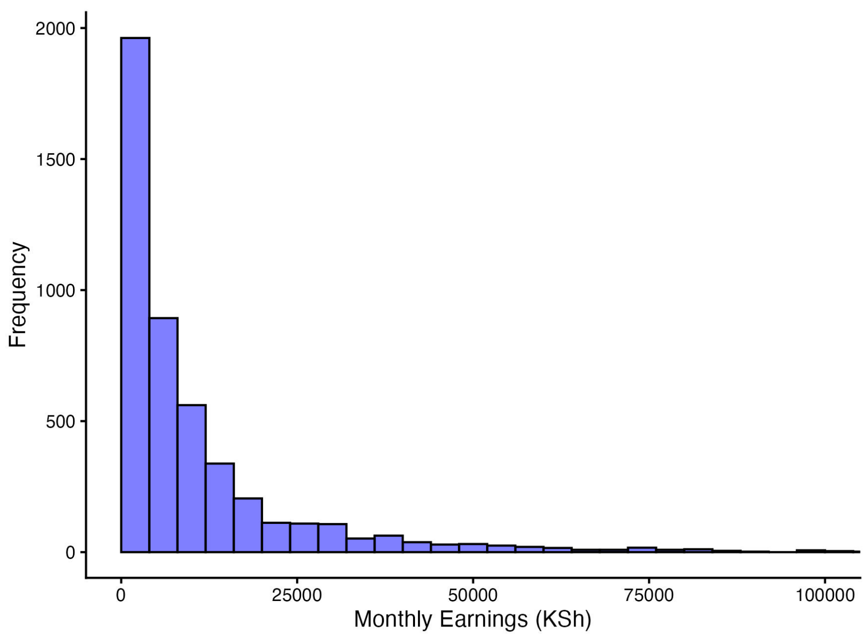
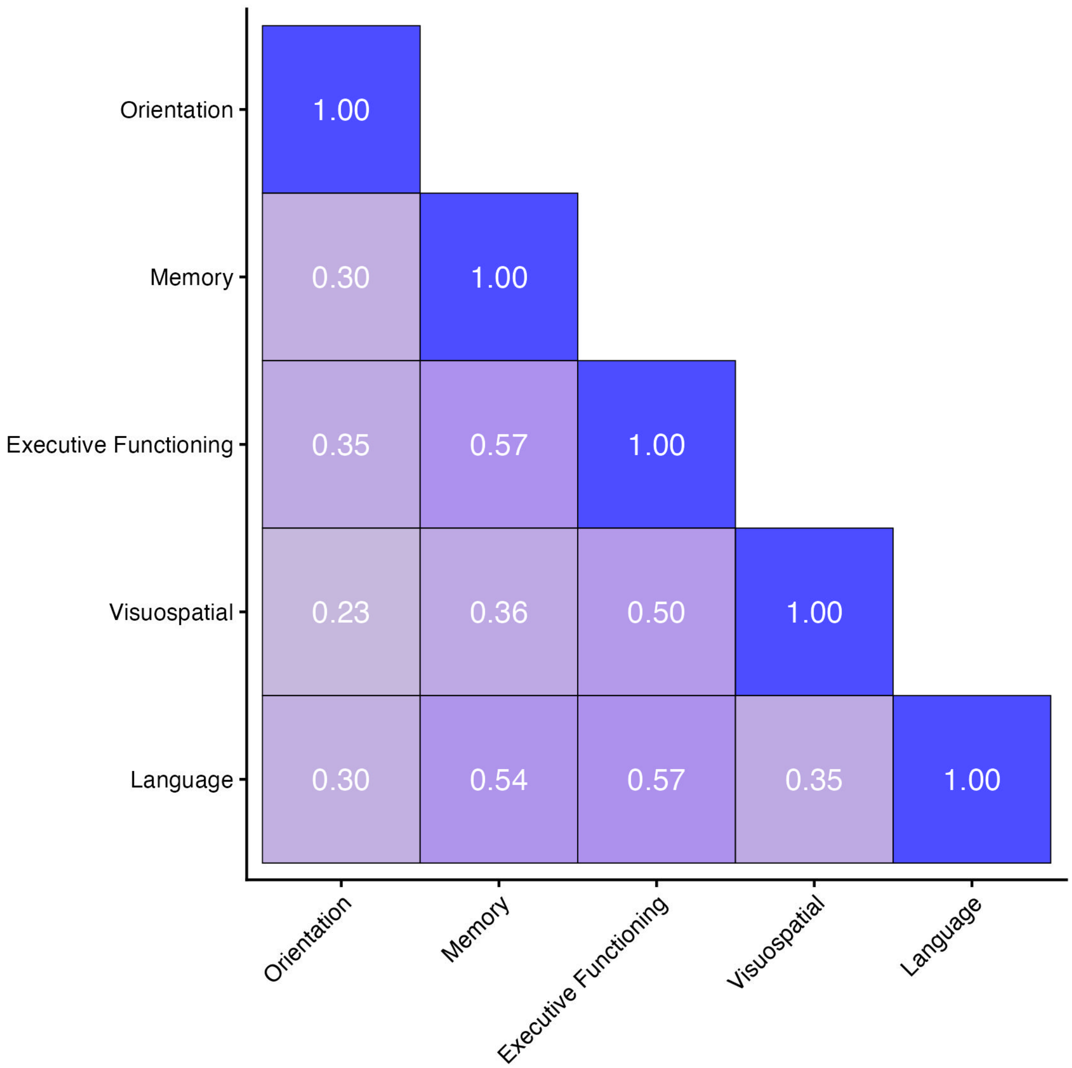


Figure A5: Distribution of Monthly Earnings, KSh (KLPS-5)



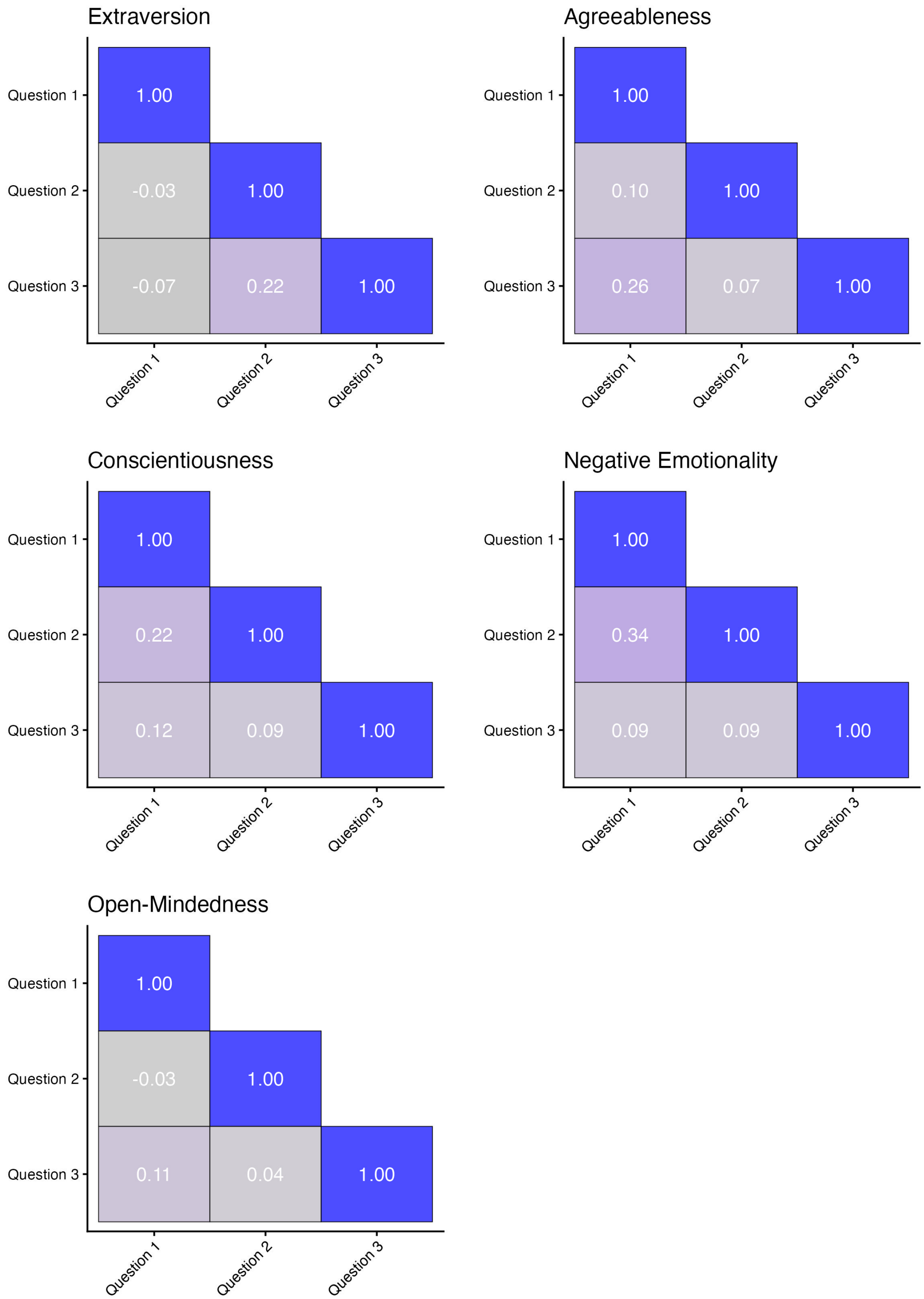
Histogram censored at 100,000 KSh for ease of readability.

Figure A6: Pairwise Correlations of HCAP Cognitive Indices



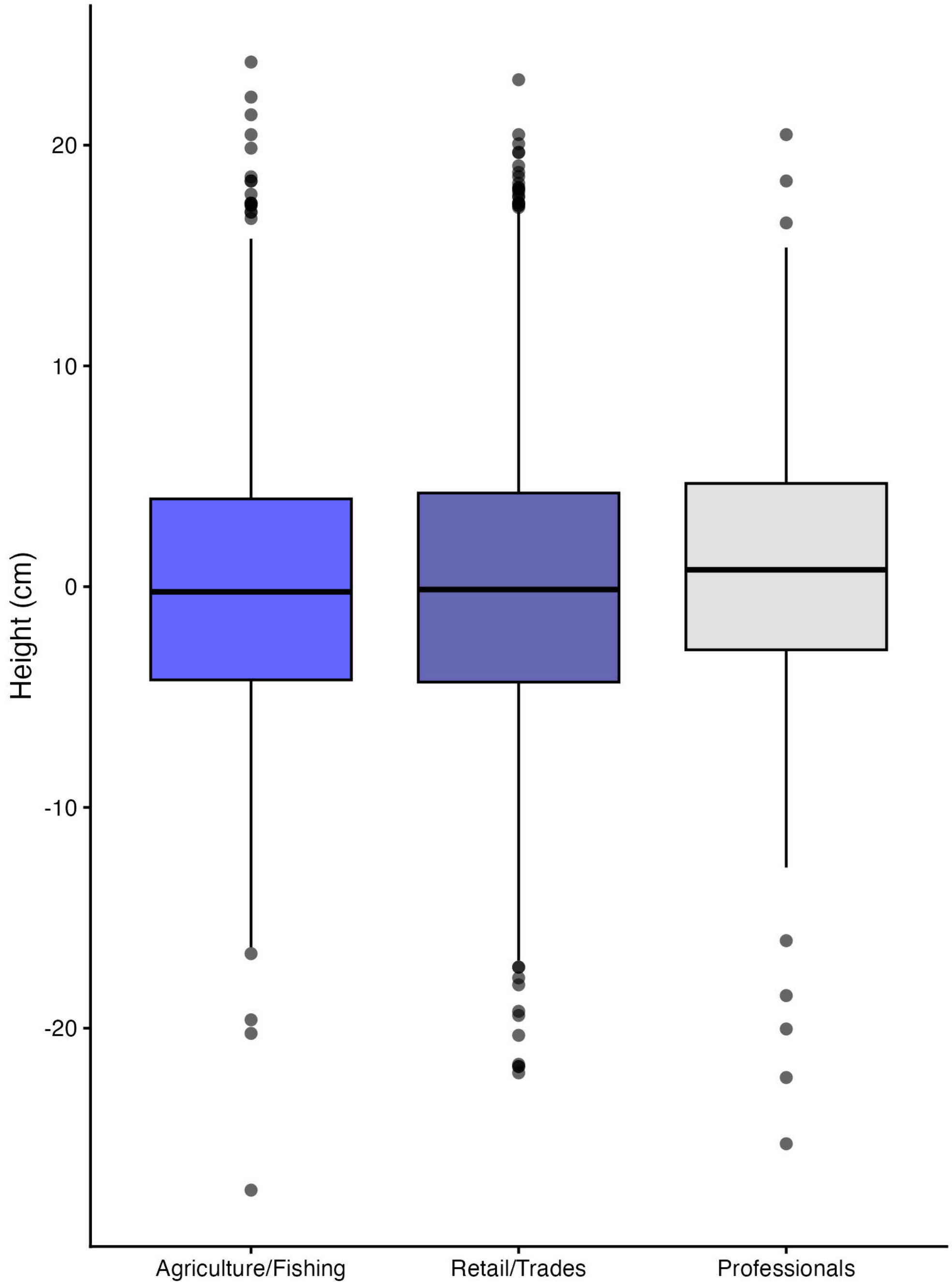
This figure plots pair-wise correlations between each of the five cognitive indices leveraged in our analysis.

Figure A7: Itemwise Correlations of Personality Questions



This figure plots pair-wise correlations between survey questions used to assess each of the "Big Five" personality traits in our data. All survey questions take values from 1 ("Disagree strongly") to 5 ("Agree strongly").

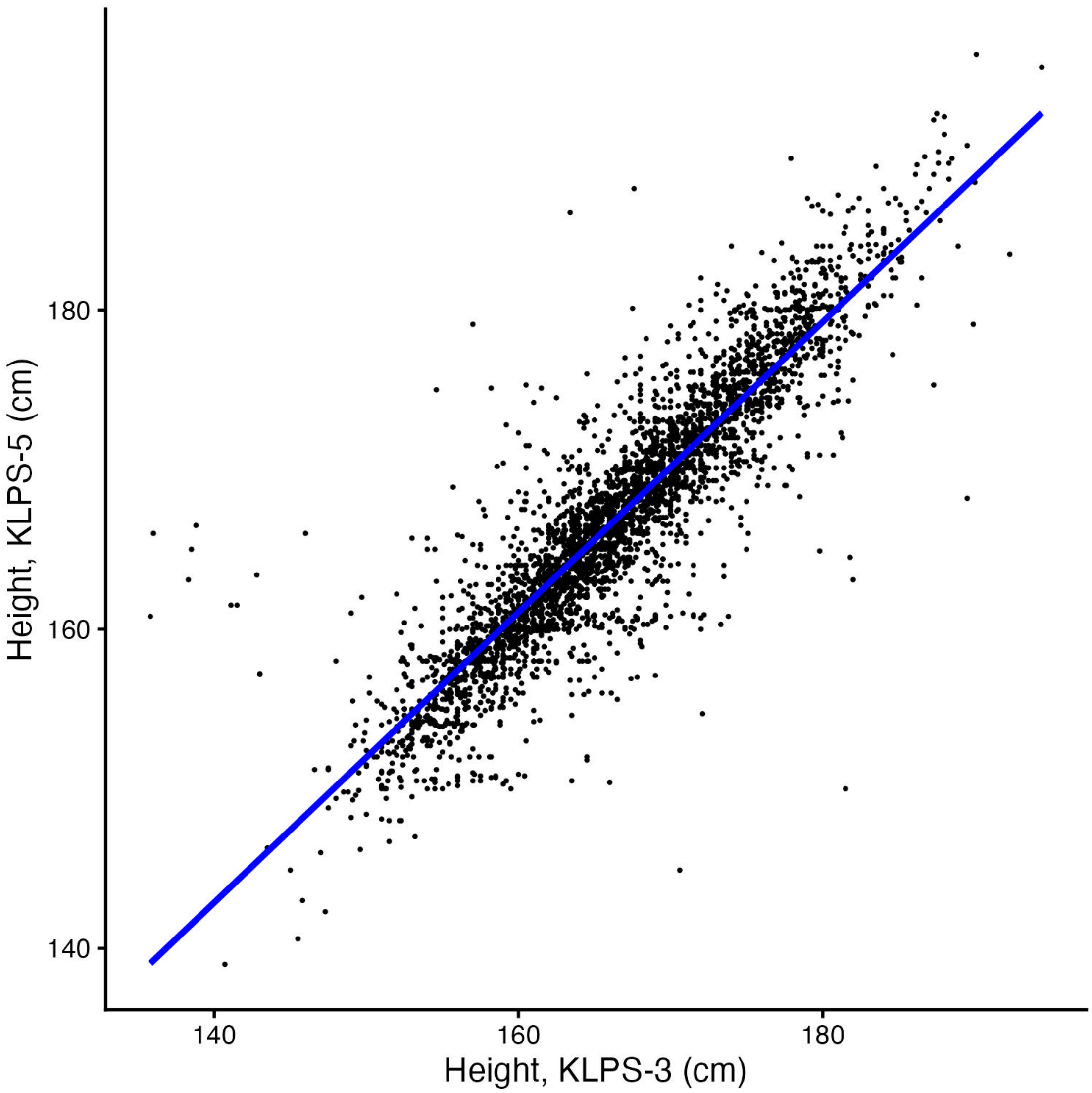
Figure A8: Distribution of Heights Within and Across Occupations



This figure plots the distribution of heights (residualized of respondent gender) within three classes of occupations in the KLPS-5 sample. Boxes correspond to the interquartile range (IQR) of height. Whiskers extend to 1.5 times the IQR. Respondents with heights less than 110 cm are excluded, as in the main analysis.

A.5 Measurement Error

Figure A9: Correlation Between Height (cm) in KLPS-3 vs. KLPS-5



This figure plots the relationship between heights as measured in KLPS-3 and KLPS-5, for the subset of respondents where height is available in both surveys. Respondents with height less than 110 cm in either survey are excluded, as in the main analysis. Pearson correlation coefficient: ρ =0.90.

Table A1: Instrumental Variables Estimates, Cognition and the Height/Earnings Premium

	Logged Earnings						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: OLS Estimates							
Height (cm)	0.0099***	0.0065*	0.0066*	0.0061*	0.0062*	0.0063*	0.0055
	(0.0035)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)
Observations	3,643	3,643	3,643	3,643	3,643	3,643	3,643
Adjusted R^2	0.240	0.252	0.272	0.289	0.289	0.291	0.300
Panel B: IV Estimates							
Height (cm)	0.0109***	0.0106***	0.0093**	0.0076*	0.0077*	0.0078**	0.0073*
	(0.0041)	(0.0041)	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0039)
Orientation		0.3368***	0.2060***	0.1093**	0.1123**	0.0999**	0.1006**
		(0.0457)	(0.0460)	(0.0458)	(0.0457)	(0.0460)	(0.0463)
Memory			0.2550***	0.1188***	0.1227***	0.0932***	0.0763**
			(0.0265)	(0.0291)	(0.0293)	(0.0306)	(0.0305)
Executive Functioning				0.3157***	0.3301***	0.2937***	0.2517***
				(0.0335)	(0.0357)	(0.0368)	(0.0375)
Visuospatial					−0.0452	−0.0538	−0.0861**
					(0.0376)	(0.0379)	(0.0383)
Language Fluency						0.1302***	0.1033**
						(0.0410)	(0.0408)
Years of Schooling							0.0592***
							(0.0090)
Respondent Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FEs	No	No	No	No	No	No	No
Observations	3,643	3,643	3,643	3,643	3,643	3,643	3,643
Adjusted R^2	0.240	0.252	0.272	0.289	0.289	0.291	0.300
First Stage F-Statistic	9002.39	8998.56	8996.83	8974.55	8971.15	8969.36	8965.81

Panel A corresponds to the same set of controls as Panel B, estimated via OLS rather than IV. Sample is restricted to the subset of KLPS-5 respondents for which height in KLPS-3 is available. Observations are dropped if height is recorded as less than 110 cm in either KLPS-3 or KLPS-5. All regressions include demographics including gender, religion, age, tribe, and location. Robust standard errors in parentheses. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

Table A2: Instrumental Variables Estimates, Childhood Background, Non-Cognitive Abilities and the Height/Earnings Premium

	Logged Earnings				
	(1)	(2)	(3)	(4)	(5)
Panel A: OLS Estimates					
Height (cm)	0.0055	0.0055	0.0053	0.0043	0.0034
	(0.0034)	(0.0034)	(0.0033)	(0.0034)	(0.0030)
Observations	3,643	3,643	3,643	3,643	3,643
Adjusted R^2	0.300	0.303	0.312	0.312	0.459
Panel B: IV Estimates					
Height (cm)	0.0073*	0.0072*	0.0066*	0.0057	0.0063*
	(0.0039)	(0.0039)	(0.0039)	(0.0040)	(0.0036)
Secondary Education: Father		0.0969**	0.0947**	0.0953**	0.0488
		(0.0466)	(0.0464)	(0.0464)	(0.0420)
Secondary Education: Mother		0.1610***	0.1478**	0.1515**	0.0579
		(0.0605)	(0.0602)	(0.0603)	(0.0526)
Extroversion			0.1504***	0.1478***	0.1332***
			(0.0288)	(0.0288)	(0.0261)
Agreeableness			−0.0875**	−0.0892**	−0.0701**
			(0.0388)	(0.0389)	(0.0349)
Conscientiousness			0.0930**	0.0920**	0.0720**
			(0.0380)	(0.0380)	(0.0341)
Negative Emotionality			−0.0210	−0.0203	−0.0232
			(0.0272)	(0.0272)	(0.0239)
Open Mindedness			0.0425	0.0400	0.0379
			(0.0324)	(0.0325)	(0.0292)
Grip Strength				0.0044	0.0036
				(0.0035)	(0.0031)
Respondent Demographics	Yes	Yes	Yes	Yes	Yes
Cognitive Controls	Yes	Yes	Yes	Yes	Yes
Occupation FEs	No	No	No	No	Yes
Observations	3,643	3,643	3,643	3,643	3,643
Adjusted R^2	0.300	0.303	0.312	0.312	0.459
First Stage F-Statistic	8965.81	8966.3	8955.69	8581.02	8475.24

Panel A corresponds to the same set of controls as Panel B, estimated via OLS rather than IV. Sample is restricted to the subset of KLPS-5 respondents for which height in KLPS-3 is available. Observations are dropped if height is recorded as less than 110 cm in either KLPS-3 or KLPS-5. All regressions include variables for cognitive controls, as in Table 2. Respondent demographics include gender, religion, age, tribe, and location. Robust standard errors in parentheses. $^{*}p < .10, ^{**}p < .05, ^{***}p < .01$.

A.6 Controlling for Prior Measures of Cognition

Table A3: Present and Past Cognition and the Height/Earnings Premium

	Logged Earnings				
	(1)	(2)	(3)	(4)	(5)
Height (cm)	0.0064**	0.0064**	0.0061**	0.0061**	0.0060**
	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
Executive Functioning	0.4001***	0.3766***	0.3139***	0.3216***	0.2808***
	(0.0280)	(0.0287)	(0.0317)	(0.0332)	(0.0340)
Orientation		0.1036***	0.0814**	0.0831**	0.0664
		(0.0400)	(0.0402)	(0.0402)	(0.0404)
Memory			0.1109***	0.1132***	0.0802***
			(0.0256)	(0.0257)	(0.0268)
Visuospatial				−0.0268	−0.0357
				(0.0336)	(0.0337)
Language Fluency					0.1509***
					(0.0357)
Raven's Score (KLPS-2/3)	0.0674***	0.0686***	0.0626***	0.0645***	0.0597**
	(0.0239)	(0.0239)	(0.0238)	(0.0239)	(0.0239)
Respondent Demographics	Yes	Yes	Yes	Yes	Yes
Occupation FEs	No	No	No	No	No
Observations	4,576	4,576	4,576	4,576	4,576
Adjusted R^2	0.296	0.297	0.300	0.300	0.302

The outcome is logged earnings in the previous 30 days, summing across agriculture and income from wages and businesses. Cognitive indices are standardized to have mean zero and standard deviation one. Respondent demographics include gender, religion, age, tribe, and location. Robust standard errors in parentheses. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

A.7 Heterogeneity by Gender

Table A4: Height and Cognitive Ability by Gender

	Logged Earnings							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Height (cm)	0.0081*	0.0064	0.0044	0.0043	0.0036	0.0036	0.0037	0.0032
	(0.0043)	(0.0042)	(0.0042)	(0.0042)	(0.0041)	(0.0041)	(0.0041)	(0.0041)
Height (cm) × Female	0.0051	0.0039	0.0040	0.0043	0.0049	0.0050	0.0044	0.0044
	(0.0062)	(0.0061)	(0.0060)	(0.0060)	(0.0059)	(0.0059)	(0.0059)	(0.0059)
Female	−1.7830*	−1.4878	−1.4946	−1.5469	−1.6602*	−1.6812*	−1.5911	−1.5714
	(1.0330)	(1.0210)	(1.0032)	(1.0010)	(0.9965)	(0.9971)	(0.9920)	(0.9844)
Executive Functioning			0.4349***	0.4126***	0.3434***	0.3497***	0.3058***	0.2654***
			(0.0261)	(0.0266)	(0.0299)	(0.0317)	(0.0326)	(0.0332)
Orientation				0.1012**	0.0782*	0.0794**	0.0624	0.0667*
				(0.0399)	(0.0402)	(0.0401)	(0.0403)	(0.0405)
Memory					0.1165***	0.1183***	0.0840***	0.0686**
					(0.0256)	(0.0258)	(0.0269)	(0.0268)
Visuospatial						−0.0199	−0.0296	−0.0581*
						(0.0335)	(0.0337)	(0.0340)
Language Fluency							0.1550***	0.1279***
							(0.0357)	(0.0355)
Years of Schooling								0.0571***
								(0.0079)
Respondent Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FEs	No	No	No	No	No	No	No	No
Observations	4,576	4,576	4,576	4,576	4,576	4,576	4,576	4,576
Adjusted R^2	0.246	0.266	0.295	0.295	0.299	0.298	0.301	0.309

The outcome is logged earnings in the previous 30 days, summing across agriculture and income from wages and businesses. Cognitive indices are standardized to have mean zero and standard deviation one. Respondent demographics include gender, religion, age, tribe, and location. Robust standard errors in parentheses. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

Table A5: Height, Childhood Background, and Non-Cognitive Ability by Gender

	Logged Earnings				
	(1)	(2)	(3)	(4)	(5)
Height (cm)	0.0032	0.0032	0.0031	0.0019	0.0037
	(0.0041)	(0.0041)	(0.0040)	(0.0041)	(0.0038)
Height (cm) × Female	0.0044	0.0042	0.0036	0.0037	−0.0004
	(0.0059)	(0.0059)	(0.0058)	(0.0058)	(0.0052)
Female	−1.5714	−1.5456	−1.3821	−1.3559	−0.5596
	(0.9844)	(0.9830)	(0.9710)	(0.9712)	(0.8763)
Secondary Education: Father		0.1008**	0.0965**	0.0971**	0.0487
		(0.0418)	(0.0416)	(0.0416)	(0.0376)
Secondary Education: Mother		0.1324**	0.1198**	0.1226**	0.0440
		(0.0533)	(0.0530)	(0.0531)	(0.0471)
Extroversion			0.1268***	0.1237***	0.1017***
			(0.0257)	(0.0258)	(0.0232)
Agreeableness			−0.1099***	−0.1117***	−0.0826***
			(0.0347)	(0.0348)	(0.0311)
Conscientiousness			0.1214***	0.1194***	0.1017***
			(0.0335)	(0.0335)	(0.0303)
Negative Emotionality			−0.0166	−0.0163	−0.0149
			(0.0238)	(0.0238)	(0.0210)
Open Mindedness			0.0615**	0.0584**	0.0430*
			(0.0284)	(0.0285)	(0.0257)
Grip Strength				0.0052*	0.0046*
				(0.0030)	(0.0027)
Respondent Demographics	Yes	Yes	Yes	Yes	Yes
Cognitive Controls	Yes	Yes	Yes	Yes	Yes
Occupation FEs	No	No	No	No	Yes
Observations	4,576	4,576	4,576	4,576	4,576
Adjusted R^2	0.309	0.312	0.321	0.321	0.462

The outcome is logged earnings in the previous 30 days, summing across agriculture and income from wages and businesses. All regressions include cognitive measures, as in Table 2. Personality measures are discrete indices taking values 0-15, standardized in the analysis sample to have mean zero and standard deviation one. Occupation fixed effects include indicators for 48 distinct primary occupations. Respondent demographics include gender, religion, age, tribe, and location. Robust standard errors in parentheses. $^{*}p < .10, ^{**}p < .05, ^{***}p < .01$.

A.8 Controlling for Self-Reported Work Hours

Table A6: Cognition and the Height/Earnings Premium, Controlling for Self-Reported Work Hours

	Logged Earnings						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Height (cm)	0.0098***	0.0060**	0.0060**	0.0056**	0.0056**	0.0055**	0.0050*
	(0.0029)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)
Hours Worked	0.0042***	0.0040***	0.0040***	0.0040***	0.0040***	0.0040***	0.0040***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Executive Functioning		0.3949***	0.3758***	0.3049***	0.3049***	0.2618***	0.2248***
		(0.0248)	(0.0255)	(0.0285)	(0.0303)	(0.0311)	(0.0315)
Orientation			0.0869**	0.0633*	0.0633*	0.0467	0.0507
			(0.0374)	(0.0376)	(0.0376)	(0.0379)	(0.0381)
Memory				0.1192***	0.1192***	0.0856***	0.0714***
				(0.0238)	(0.0239)	(0.0249)	(0.0248)
Visuospatial					0.0002	−0.0094	−0.0361
					(0.0309)	(0.0310)	(0.0313)
Language Fluency						0.1521***	0.1271***
						(0.0330)	(0.0329)
Years of Schooling							0.0529***
							(0.0074)
Respondent Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FEs	No	No	No	No	No	No	No
Observations	4,576	4,576	4,576	4,576	4,576	4,576	4,576
Adjusted R^2	0.347	0.387	0.388	0.391	0.391	0.394	0.401

The outcome is logged earnings in the previous 30 days, summing across agriculture and income from wages and businesses. Hours worked denotes the sum of self-reported work hours in the previous week across agriculture, self-employment, and formal employment, multiplied by 4.29. Cognitive indices are standardized to have mean zero and standard deviation one. Respondent demographics include gender, religion, age, tribe, and location. Robust standard errors in parentheses. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

Table A7: Height, Childhood Background, and Non-Cognitive Ability, Controlling for Self-Reported Work Hours

	Logged Earnings				
	(1)	(2)	(3)	(4)	(5)
Height (cm)	0.0050*	0.0049*	0.0045*	0.0037	0.0034
	(0.0028)	(0.0028)	(0.0027)	(0.0028)	(0.0026)
Hours Worked	0.0040***	0.0040***	0.0040***	0.0040***	0.0032***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Secondary Education: Father		0.1021***	0.0979**	0.0983**	0.0490
		(0.0388)	(0.0387)	(0.0387)	(0.0356)
Secondary Education: Mother		0.1050**	0.0937*	0.0956*	0.0425
		(0.0501)	(0.0498)	(0.0498)	(0.0457)
Extroversion			0.1146***	0.1127***	0.0959***
			(0.0242)	(0.0242)	(0.0217)
Agreeableness			−0.1046***	−0.1059***	−0.0796***
			(0.0322)	(0.0323)	(0.0299)
Conscientiousness			0.0970***	0.0956***	0.0805***
			(0.0306)	(0.0307)	(0.0282)
Negative Emotionality			−0.0105	−0.0103	−0.0067
			(0.0221)	(0.0221)	(0.0200)
Open Mindedness			0.0617**	0.0597**	0.0436*
			(0.0265)	(0.0266)	(0.0239)
Grip Strength				0.0037	0.0046*
				(0.0029)	(0.0026)
Respondent Demographics	Yes	Yes	Yes	Yes	Yes
Cognitive Controls	Yes	Yes	Yes	Yes	Yes
Occupation FEs	No	No	No	No	Yes
Observations	4,576	4,576	4,576	4,576	4,576
Adjusted R^2	0.401	0.403	0.410	0.410	0.512

The outcome is logged earnings in the previous 30 days, summing across agriculture and income from wages and businesses. Hours worked denotes the sum of self-reported work hours in the previous week across agriculture, self-employment, and formal employment, multiplied by 4.29. All regressions include cognitive measures, as in Table 2. Personality measures are discrete indices taking values 0-15, standardized in the analysis sample to have mean zero and standard deviation one. Occupation fixed effects include indicators for 48 distinct primary occupations. Respondent demographics include gender, religion, age, tribe, and location. Robust standard errors in parentheses. $^{*}p < .10,^{**} p < .05,^{***} p < .01$.

B Survey Questions

B.1 Cognitive Measures

Cognitive indices are constructed from responses to 27 distinct modules of cognitive survey questions. Responses are aggregated into domain scores (for executive functioning, orientation, language/fluency, memory, and visuospatial functioning, respectively) and a general cognitive score using Confirmatory Factor Analysis (CFA), a method commonly applied in the psychology literature. For further detail on the construction of these indices in KLPS-5, see Gross et al. (2025). Listed below are a subset of the cognitive modules employed, with short descriptions reproduced from the Supplemental Information of Gross et al. (2025). Modules are drawn from the standard HCAP protocol, with some questions adapted to fit the local Kenyan context (e.g. respondents, when asked to describe the similarities and differences between two items, are asked about "kale" and "spinach" — common leafy greens in Kenya — rather than "roses" and "daises," as in the standard HCAP).

- Swahili Mental State Exam (Orientation)
  - Description: This test is an adaptation of other mental state exams that is adapted for Swahili-speaking populations (such as those in KLPS), evaluating domains such as temporal orientation (today's date, month, year, and season), spatial orientation (place), registration, attention, recall and speech.
- Object Naming (Language/Fluency)
  - Description: This test involved three questions on items that should be considered common for the participants.
- Symbol Cancellation Test (Executive Functioning)
  - Description: This cognitive assessment tool evaluates visual selective attention, requiring participants to identify and mark specific target symbols from a larger array of distractor symbols within one minute.
- Community Screening Instrument for Dementia (CSI-D) (Language/Fluency)
  - Description: This is a test commonly used for detecting dementia in community settings.
- Raven's Progressive Matrices Test (Executive Functioning)

- Description: This cognitive test measures abstract reasoning and non-verbal intelligence, particularly fluid intelligence, which involves reasoning and problem-solving skills that are independent of acquired knowledge.

- Digit Span Tests (Executive Functioning)
  - Description: These are cognitive assessments used to measure verbal short-term and working memory. The numbers were read to the participants in a monotonic nature (said in a continuous prose without tonal variation).
- Similarities and Differences: Judgement and Problem-Solving (Executive Functioning)
  - Description: This test involves identifying similarities and differences between various concepts, objects, or ideas. The test is used to assess abstract reasoning, verbal comprehension and conceptual thinking.
- 10 Word List Recall (Memory)
  - Description: This test assesses verbal memory through word recall.
- Found a Lost Child (Executive Functioning)
  - Description: This test assesses cognitive abilities in real-world contexts, using cognitive functions like problem solving, executive functioning, and social cognition.
- Logical Memory Story #2 (East Boston Story) (Memory)
  - Description: Part of the Wechsler Memory Scale (WMS), this test assesses verbal memory through story recall.
- Constructional Praxis (Visuospatial, Memory)
  - Description: This test assesses the ability to construct or assemble objects, involving motor skills and visual and spatial perception.
- Go-No-Go Trial (Executive Functioning)
  - Description: This test measures the ability to control impulsive responses, assessing executive functioning, response inhibition, attention, focus, and impulse control.

- Token Test (Executive Functioning)
  - Description: This assessment evaluates auditory comprehension and language processing abilities.

B.2 Big 5 Personality Measures

Now I will read a list of statements that may or may not apply to you. Please show me whether you agree strongly, agree a little, feel neutral/no opinion, disagree a little or disagree strongly. Codes are as follows: 1 = Disagree strongly; 2 = Disagree a little; 3 = Neutral: no opinion; 4 = Agree a little; 5 = Agree strongly. To construct our measure of each personality trait, we sum the codes for all relevant questions, and standardize within sample such that the final index has mean zero and standard deviation one.

Table B1: Survey Questions for "Big 5" Measures

#	Question	Personality Trait	Reverse Coded
1	Tends to be quiet	Extroversion	✓
2	Is compassionate, has a soft heart	Agreeableness	
3	Tends to be disorganized	Conscientiousness	✓
4	Worries a lot	Negative Emotionality	
5	Is fascinated by art, music, literature	Open Mindedness	
6	Is dominant, acts as a leader	Extroversion	
7	Is sometimes rude to others	Agreeableness	✓
8	Has difficulty getting started on tasks	Conscientiousness	✓
9	Tends to feel depressed, blue	Negative Emotionality	
10	Has little interest in abstract ideas	Open Mindedness	✓
11	Is full of energy	Extroversion	
12	Assumes the best about people	Agreeableness	
13	Is reliable, can always be counted on	Conscientiousness	
14	Is emotionally stable, not easily upset	Negative Emotionality	✓
15	Is original, comes up with new ideas	Open Mindedness	

Questions correspond to an extra short-form Big 5 Inventory-2 (BFI-2-XS). For more detail, see Soto and John (2017).