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Does Human Capital Influence the Gender Gap in Earnings? Evidence from Four Developing Countries *

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Abstract

This paper investigates the relationship between human capital and the gender gap in earnings in four developing countries. We use high-quality panel data spanning 12 years from Ethiopia, India, Peru, and Vietnam, to construct latent stocks of cognitive and non-cognitive skills measured during adolescence. We investigate the relationship between these skills and subsequent earnings acquired in early adulthood, thereby avoiding common challenges of measurement error and simultaneity issues. Our results suggest that women earn significantly less than men in all four countries, even after accounting for differences in carefully constructed skill endowments. Interestingly, the gender gap in earnings decreases at higher cognitive skill levels in two out of the four countries. We find that these country-level variations are driven by differences in employment status as opposed to differences in earnings among the employed, and may reflect differences in unpaid care work. We further explore how the gender earnings gap varies in the context of the COVID-19 crisis. While earnings decreased for both men and women during this period, the pre-pandemic relationships between human capital and gender gaps persisted and were strengthened. By comparing the same youth cohort in different countries and periods, we elucidate the contexts under which human capital can become a force of gender convergence in the labour markets of developing countries.

Keywords: Human Capital; Gender; LMICs
JEL Classification: J24, J16

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1 Introduction

The existence of substantial gender gaps in labour market outcomes across the world has been well established in the social sciences (Klasen, 2020). Among potential determinants of this gap, human capital differences, along with social norms and housework allocation have been suggested to play a prominent role (Jayachandran 2021; Goldin 2014). However, a comprehensive investigation of these relationships necessitates databases that are extremely rare in developing countries. First, such analysis requires to properly measure cognitive and non-cognitive skills, which is particularly challenging in the context of developing countries (Lajaaj & Macours, 2021). Second, the analysis should ideally rely on databases connecting skill measures that predate labour market outcomes to avoid simultaneity issues. Yet, longitudinal studies are rare, in particular in developing countries. Therefore, the literature often uses human capital proxies based on the quantity of schooling or skills measures that are contemporaneous to labour market outcomes (Rebollo-Sanz & De la Rica 2020; Hanushek et al. 2015).

This paper fills that gap by exploiting unique panel data that tracks a cohort of individuals from adolescence into adulthood in Ethiopia, India (Andhra Pradesh and Telangana sites), Peru and Vietnam. We investigate the role of human capital in explaining gender gaps in labour market outcomes for youth samples in these four developing countries during regular economic conditions and during a global crisis. To do so, we leverage high-quality measures of human capital that capture cognitive and non-cognitive skills during adolescence. For the former, we make use of mathematics, reading and vocabulary test scores, administered to both those attending and out of school. The latter measures consist of survey-based indicators of a broad range of socio-emotional skills. Importantly, these instruments were carefully validated for a developing country context (Lajaaj & Macours, 2021).

To carry out this analysis, we first estimate latent stocks of cognitive and non-cognitive skills, employing exploratory factor analysis in order to minimize measurement error. We then estimate the conditional relationship between labor market outcomes and pre-labour market skill measures, thereby avoiding simultaneity issues. We follow recent studies analyzing labor market data such as Danon et al. (2023), Broten et al. (2022) and Powell & Seabury (2018) to focus on earnings, which cover both the extensive margin (paid employment) and the intensive margin (earnings among the employed) of labor market outcomes, although we also investigate these margins separately. Our focus on earnings derives primarily from its ability to represent an individual's command over resources. This underscores the empowerment aspect of labour market outcomes, a central angle for the analysis of gender gaps. Due to the skewed nature of this variable and the non-negligible share of zero earners in our data, we estimate poisson pseudo-maximum-likelihood models (PPML), following Broten et al. (2022) and Powell

& Seabury (2018). Note that while we make a serious attempt to reduce biases that may obfuscate the patterns of interest, our main interest is on the descriptive patterns that emerge between the gender gap in earnings and our skills measures. First, we document the size of the gender gap in earnings of 26-27 year olds and investigate whether it closes after accounting for differences in human capital. In short, it does not. Gender gaps favoring men remain significant in all four countries after adjusting for differences in cognitive and non-cognitive skills. Notably, women acquire lower earnings than men at virtually every level of cognition in all samples. We further show that cognitive skills, unlike noncognitive skills, are systematic predictors of earnings.

We then investigate whether the gender gap in earnings varies across different human capital levels. While a closing gap for the highly skilled seems arguably intuitive, the gap may still persist in the face of rigid and patriarchal social norms. Our estimates suggest that the gap narrows at higher levels of cognition in Ethiopia and Peru, an effect that seems to be driven by variation in paid employment status, rather than by variation among earners. At the same time, the gender gap is not systematically affected by cognitive skills in India and Vietnam. That is, returns to cognitive skills are larger for women in two out of the four countries. We provide suggestive evidence that gender disparities in household work underlies this cross-country evidence. Overall, these results suggest that human capital is a force of partial gender convergence in country samples that have a lower share of women engaging in unpaid care work.[1]

Lastly, we substantiate our analysis by investigating whether the relationship between human capital and earnings changes in the context of the COVID-19 pandemic, a period when economic distress and social norms surrounding care work may be more salient. While average earnings drop, returns to cognitive skills increase in the most critical phases of the COVID-19 pandemic, suggesting that skills contribute to the labour market resilience of the youth against negative macroeconomic shocks. Interestingly, the differential returns to human capital by gender are accentuated during the crisis.

While a handful of other studies have advanced our understanding on the role of human capital and gender gaps in labour market outcomes in the context of developing countries, this is, to the best of our knowledge, the first analysis within that literature that investigates how measures of cognitive and non-cognitive skills predating labour market activity are associated with the gender gap in total earnings. A paper more closely related to ours is Glewwe et al. (2022), who uses skills data predating labour market outcomes from rural China to show that cognitive and non-cognitive skills are predictive of logged hourly wages at the ages of 24-27 years old, with differing effects of non-cognitive skills across genders.[2] The extensive margin of labour market outcomes remains unexplored,

[1]See Jayachandran (2021) for a broader discussion on the role of home production and social norms in the labor market outcomes of women.

[2]Glewwe et al. (2017) runs a similar analysis with the same sample but at the ages of 17-21 years, when formal education is not fully completed for those enrolling in tertiary education.

which is not surprising considering that the primary emphasis of the analysis does not lie on gender differences. A second related study investigates the returns to skills in rural Pakistan, with cognitive and non-cognitive skills measured contemporaneously with labour market outcomes (Danon et al. 2023). While gender differences are not the main focus of the paper, the analysis is similar to ours in the use of factor analysis for the construction of skill measures.[3]

We add to this slim literature in a number of conceptual ways. First, we are the first to focus on total earnings, a particularly relevant indicator for gender studies as it embodies the command of individuals over economic resources. This indicator allows us to study the association between skills and the extensive and intensive margin of labour market outcomes both combined and separately. We avoid typical estimation challenges that come with a non-negative skewed dependent variable by using PPML models, following Broten et al. (2022) and Powell & Seabury (2018) and as suggested by Santos Silva & Tenreyro (2006).

Second, we are the first to explore how these relationships behave when a period of economic distress kicks in. A narrower literature has analysed how returns to skills are impacted by broader macroeconomic changes. Rosas et al. (2017) show that returns to cognitive and non-cognitive skills increased among the urban youth in Sierra Leone during the Ebola crisis. Hershbein & Bahn (2018) observe an increase in job postings that demand higher-order cognitive skills during the great economic recession in the US. We add to the literature by exploring how the returns to human capital and the gender gap are impacted by a global economic and health crisis. Our focus on young cohorts is of particular relevance for policy, given that these groups of workers may be more adversely impacted by the economic conditions of the pandemic .

Third, we are the first analysis of the aforementioned gender literature in developing countries to simultaneously consider three different dimensions of human capital: cognitive skills, non-cognitive skills, and a health proxy, which are often regarded as the three major components of human capital (Attanasio, 2015). With this, we also add to the larger literature on the returns to multidimensional human capital. Previous studies have analysed sub-components of human capital in different contexts. Cognitive and non-cognitive skills have been studied in Sweden (Edin et al. 2022; Lindvist & Vestman 2011), rural China (Glewwe et al. 2022) and rural Pakistan (Danon et al. 2023), whilst cognitive skills and health stocks have been studied in Mexico (Vogl 2014), Indonesia (Lafave & Thomas 2017), the United States and the United Kingdom (Case & Paxon, 2008).

[3]Nordman et al. (2019) and Tognatta et al. (2016) investigate gender gaps in hourly wages with a sample of employed individuals. They use the same instruments to measure skills and relate them to contemporaneous labor market outcomes in Bangladesh and 7 countries participating in the World Bank STEP survey. However, as indicated by Tognatta et al. (2016), the validity of the skill measures is limited.

The richness of our dataset allows us to advance the literature on various estimation aspects as well. Next to Glewwe et al. (2022), we are the second to use skill measures that predate labour market outcomes, thereby resolving potential simultaneity concerns. In this respect, the cohort structure of the data allows us to circumvent empirical issues associated with differences in life-cycles across individuals. Furthermore, we contribute by estimating latent stocks of skills similar to Danon et al. (2023), by relying on a comprehensive battery of measurement items that were previously validated in each of the study countries, thus accounting for the multidimensional nature of skills and imperfect measurements (Lajaaj & Macours, 2021; Cunha & Heckman, 2007; Cunha et al., 2010).

2 Data and descriptive statistics

2.1 Data

We utilize data from the Young Lives study, a panel survey conducted in Ethiopia, India (Andhra Pradesh and Telangana states), Peru and Vietnam. The survey was first administered in 2002. This was followed up by four rounds of in-person data collection in 2006, 2009, 2013 and 2016 and a five-calls phone surveys in 2020-2021. Our analysis focuses on the older cohort who were 26-27 years old during the phone surveys (first surveyed aged 8 in 2002). At this age, most individuals would have completed a substantial portion of their schooling, and so we can link human capital with labour market outcomes. Note that the cohort structure of the sample permits us to avoid empirical challenges associated with life-cycle disparities within a given sample.

We use data collected in-person in 2009 (age 15), 2013 (age 19), and 2016 (age 22) to compute the indicators for human capital stocks and other socioeconomic variables. We use data from the 2020-21 phone surveys for the labour market outcomes, observing the measures at three points in time: i) Wave 1 in December 2019 - February 2020, just before the pandemic ii) Wave 2 in August-October 2020, when the crisis restricted mobility the most in India and Peru iii) Wave 3 in October-December 2021, when mobility was back to normal in India and Peru but more restricted in Vietnam. [4]

The Young Lives sample was selected using a multi-stage sampling procedure during the first round in 2002. In each country, 20 sentinel sites were selected, with poorer areas purposely over-sampled. Within each site, households with children between the age 7 and 8 were chosen – 1000 households were sampled in Ethiopia, India, and Vietnam and 700 households were sampled in Peru. By 2016, when the last in-person data collection of human capital measures took place, the total sample consisted of 3254 individuals

[4]Most of the analysis presented here makes use of the first time period, except for the section exploring the evolution of coefficients over time. Note that pre-pandemic labour market outcomes are collected retrospectively. See Figure A1 in the appendix for a depiction of mobility trends in India, Peru and Vietnam.

in the four countries. Note that the phone surveys were administered during a global pandemic and, the last of them, during an armed conflict in Ethiopia. A total of 204 individuals were not included in the phone survey, resulting in 3050 individuals across the four countries observed in at least one of the three waves. [5]

Employment and net earnings definitions

Given our focus on the gender earnings gap, rather than focusing on formal definitions of employed and unemployed, we distinguish those who have non-zero earnings from their own labour activity as "earners". That is, those who work for payment either in cash or kind, including the self-employed. The converse of this comprises the "non-earners", which includes the unemployed as well as all others who do not work for payment. Note that this definition also implies that housewives or other non-economically active persons are included in our analysis as non-earners. However, we exclude students, the disabled and ill from our sample – a total of 156 observations across the four countries.[6]

The main labour market outcome we investigate is monthly earnings. To do so, we set the earnings of those not in employment to zero, which allows us to capture both the extensive margin of earnings – being employed or not – as well as the intensive margin of earnings among earners. These earnings are individual as opposed to household-specific, net of taxes and any other work-related payment, and in the case of self-employment, they are net of production costs. We omit the top 1% of earners in the sample to reduce the influence of outliers[7]. Furthermore, we transform local currency units into PPP international dollars to enhance the comparability of coefficients across countries.

2.1.1 Human capital variables

Given that cognitive and non-cognitive skills are multidimensional and unobservable, we estimate latent stocks of these skills for each individual (Attanasio et al., 2017; Glewwe et al., 2017; Heckman et al., 2006). To do so, we assume these skills can be proxied with error by existing observable measures, and we specify a linear relationship between the observable and the latent skills. In the appendix, we describe the initial exploratory factor analysis that suggests we extract two factors that comprise cognitive and non-cognitive skills, and we specify the measurement system used to estimate these latent skills from the observable measures. We use maximum likelihood to estimate the measurement

[5]Attrition analysis, which is available upon request, suggests that attrition is random in India and not random in Ethiopia, Peru, and Vietnam. For the Ethiopian sample, individuals of the Tigrian ethnicity are 10.9 percentage points less likely to participate in the survey. For the Peruvian sample, those of evangelist religion and females were 13.5 and 7.4 percentage points less likely to be in the sample. For the case of Vietnam, individuals of the Kinh ethnicity, of buddhist religion and females are 6.7, 16.6 and 4.5 percentage points less likely to participate in the survey, respectively.

[6]The 156 observations that were excluded represent 98 from Ethiopia, 30 from India, 18 from Peru and 10 from Vietnam.

[7]Our main results are robust to the inclusion of these outliers (see Table A22).

system, allowing the parameters to vary across countries. The data we use to construct these indicators were collected with measurement instruments that were carefully selected during the piloting of the survey. Items that performed poorly in standard measures of reliability were omitted.[8]

To estimate latent cognitive skills, we use scores for a math and reading comprehension test implemented at age 19 and the Peabody Picture Vocabulary Test conducted at age 15, a test that assesses receptive vocabulary abilities. Unlike many large-scale skills surveys, Young Lives administered tests at home to all participants, whether still attending school or not. The time allocated for the math and reading test was 40 and 30 minutes, respectively. The raw scores on these tests were then used to compute latent cognitive skills, with a mean of zero and standard deviation of one in each country. Note that the measures we use to construct cognitive skills might encompass the test-taker's effort, personality traits or other higher-order skills, particularly in the case of low-stakes cognitive tests (Gneezi et al. 2019).

For the respondent's non-cognitive skills, we incorporate a broad range of socio-emotional skills at age 22. These include two components measuring leadership and teamwork of the Review of Personal Effectiveness and Locus of Control (ROPELOC) self-evaluation scale (Richards et al., 2002), two scales from the Marsh Self-Description Questionnaire that assess peer relationships and general self-esteem, as well as a scale on general self-efficacy (Yorke & Ogando, 2018). There are also Duckworth and Quinn (2009) sub-scales for agency and grit, and the Big 5 components for emotional stability and conscientiousness. We provide a detailed description of these score measures in the appendix.

As health is also considered an important component of human capital, we include in our analysis a proxy for the health stocks and long-term nutrition of individuals (Attanasio 2015). For this, we use the height-for-age z-scores (HAZ) at age 15. Height measures have been suggested to signal health status. Furthermore, they have been used as crude indicators of cognition and non-cognitive skills in the absence of more sophisticated measures (LaFave & Thomas 2017, Vogl 2014, Case & Paxson 2008). As we include measures for skills in our analysis, we consider height to be a good proxy for long-term health and nutritional status. While we are not able to include the health component in the measurement system that produces the latent cognitive and non-cognitive skills, we include HAZ directly in our extended models.

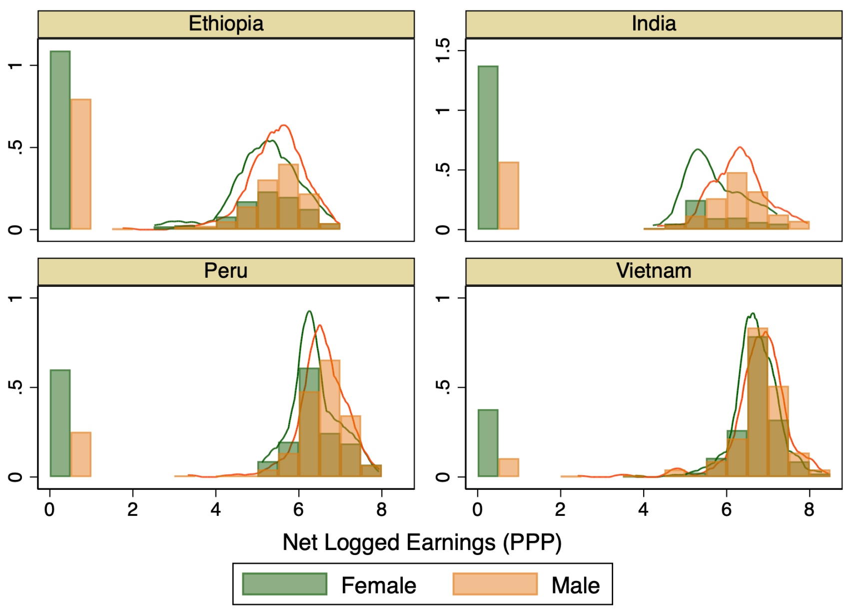
[8]For instance, of the Big Five personality traits, only instruments measuring emotional stability and conscientiousness performed satisfactory, and were therefore the only ones kept in the measurement tool.

2.2 Descriptive statistics

Table 1 presents descriptive statistics of the key variables used in the main analysis, by both gender and country. In all four countries, we observe that women on average have lower stocks of cognitive and non-cognitive skills, lower earnings and lower employment rates compared to men, with statistically significant differences. We also observe a comparatively low employment rate among men in Ethiopia, and a low female employment rate in India.

In Figure 1, we present density plots of our main outcome variable, net monthly earnings in PPP Dollars, by country and by gender. The zero earners are represented by bars at the left end, while those with positive earnings are represented by the bell-shape distribution. In all four countries, women comprise a larger proportion of the zero earners and earn less on average than men among the positive earners. Among the four countries, the gender gap in both earnings and employment appears to be the largest in India.

Figure 1: Distribution of pre-covid net earnings (PPP) by gender



In Figure 2 and 3, we present density plots of the estimated cognitive and non-cognitive skills by country and gender. In India, women appear to have lower cognitive and non-cognitive skills than men on average. In Peru, the distributions mostly overlap for men and women, suggesting that there are no substantial skill differences by gender. In Ethiopia and Vietnam, women and men have similar cognitive skills on average but slightly lower non-cognitive skills.

Table 1: Descriptive table of key variables

	Men			Women			
	Mean	SD	N	Mean	SD	N	Diff.
Ethiopia							
Urban	0.55	0.50	370	0.68	0.47	306	-0.13***
Age in months, Wave 1	314.19	3.51	370	314.35	3.51	306	-0.16
Education in years	9.97	3.68	368	10.60	3.88	305	-0.64*
Work Experience in years	11.47	4.95	370	9.25	5.67	306	2.22***
Human Capital Variables							
Non-Cognitive Skills	0.08	0.80	370	-0.24	0.87	306	0.32***
Cognitive Skills	-0.06	1.08	370	-0.11	0.96	306	0.05
Height-for-age, 2009	-1.78	1.37	365	-1.04	1.17	306	-0.74***
Labour Market Outcomes							
Net earnings (PPP), Wave 1	172.78	199.75	354	110.76	175.46	301	62.02***
Net earnings (PPP), Wave 2	129.79	188.30	359	78.65	156.11	300	51.14***
Net earnings (PPP), Wave 3	170.92	217.70	267	114.66	186.71	205	56.26**
Employment, Wave 1	0.61	0.49	366	0.46	0.50	305	0.15***
Employment, Wave 2	0.49	0.50	367	0.35	0.48	306	0.14***
Employment, Wave 3	0.51	0.50	269	0.40	0.49	208	0.11*
India							
Urban	0.31	0.46	417	0.28	0.45	439	0.02
Age in months, Wave 1	315.17	4.04	417	315.67	3.95	439	-0.49
Education in years	12.45	3.48	412	11.39	3.71	428	1.06***
Work Experience in years	8.70	4.35	417	6.68	5.40	439	2.02***
Human Capital Variables							
Non-Cognitive Skills	0.11	0.83	417	-0.19	0.91	439	0.29***
Cognitive Skills	0.07	0.95	417	-0.33	0.98	439	0.40***
Height-for-age, 2009	-1.63	1.12	416	-1.71	0.96	436	0.08
Labour Market Outcomes							
Net earnings (PPP), Wave 1	477.86	518.75	411	124.28	256.73	435	353.58***
Net earnings (PPP), Wave 2	404.03	519.21	413	107.25	249.89	433	296.79***
Net earnings (PPP), Wave 3	597.65	561.90	393	131.81	270.71	431	465.84***
Employment, Wave 1	0.72	0.45	417	0.32	0.47	439	0.40***
Employment, Wave 2	0.63	0.48	417	0.29	0.46	439	0.34***
Employment, Wave 3	0.83	0.38	399	0.35	0.48	433	0.48***

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. Highest qualification is an indicator for whether the child has pursued higher education. Urban is an indicator of whether the child lives in an urban vs. rural area. Care work before COVID is an indicator for whether the child performed care-work for household members before the pandemic. The human capital variables are z-scores. The employment variables are indicators for whether the child is employed or not.

	Men			Women			
	Mean	SD	N	Mean	SD	N	Diff.
Peru							
Urban	0.84	0.37	250	0.88	0.33	209	-0.04
Age in months, Wave 1	316.17	4.33	288	315.71	4.12	244	0.45
Education in years	13.26	2.70	248	13.11	2.90	203	0.14
Work Experience in years	8.83	3.39	283	7.76	3.74	238	1.08***
Human Capital Variables							
Non-Cognitive Skills	0.03	0.84	288	0.02	1.01	244	0.01
Cognitive Skills	0.02	0.92	288	-0.06	0.91	244	0.08
Height-for-age, 2009	-1.36	0.97	282	-1.59	0.77	242	0.24**
Labour Market Outcomes							
Net earnings (PPP), Wave 1	724.66	509.25	238	500.21	518.35	203	224.45***
Net earnings (PPP), Wave 2	673.31	603.60	235	342.73	538.11	199	330.59***
Net earnings (PPP), Wave 3	827.95	577.32	259	442.46	578.78	228	385.49***
Employment, Wave 1	0.88	0.33	248	0.70	0.46	204	0.18***
Employment, Wave 2	0.82	0.39	248	0.52	0.50	204	0.30***
Employment, Wave 3	0.91	0.28	266	0.59	0.49	233	0.32***
Vietnam							
Urban	0.42	0.49	398	0.41	0.49	420	0.01
Age in months, Wave 1	316.46	3.33	407	316.32	3.50	423	0.15
Education in years	11.70	3.33	394	12.70	3.40	415	-1.00***
Work Experience in years	9.42	3.83	407	9.29	3.77	423	0.13
Human Capital Variables							
Non-Cognitive Skills	0.08	0.83	407	-0.09	0.93	423	0.16**
Cognitive Skills	-0.05	0.91	407	-0.01	0.84	423	-0.04
Height-for-age, 2009	-1.48	0.96	398	-1.36	0.82	416	-0.12
Labour Market Outcomes							
Net earnings (PPP), Wave 1	1026.37	681.82	381	760.78	610.60	412	265.59***
Net earnings (PPP), Wave 2	995.22	686.61	376	695.38	601.30	408	299.84***
Net earnings (PPP), Wave 3	1059.98	791.70	372	746.37	732.93	392	313.61***
Employment, Wave 1	0.95	0.22	398	0.81	0.39	420	0.14***
Employment, Wave 2	0.91	0.28	398	0.76	0.43	420	0.15***
Employment, Wave 3	0.88	0.32	386	0.72	0.45	399	0.16***

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. Highest qualification is an indicator for whether the child has pursued higher education. Urban is an indicator of whether the child lives in an urban vs. rural area. Care work before COVID is an indicator for whether the child performed care-work for household members before the pandemic. The human capital variables are z-scores. The employment variables are indicators for whether the child is employed or not.

Figure 2: Distribution of latent cognitive skills by gender

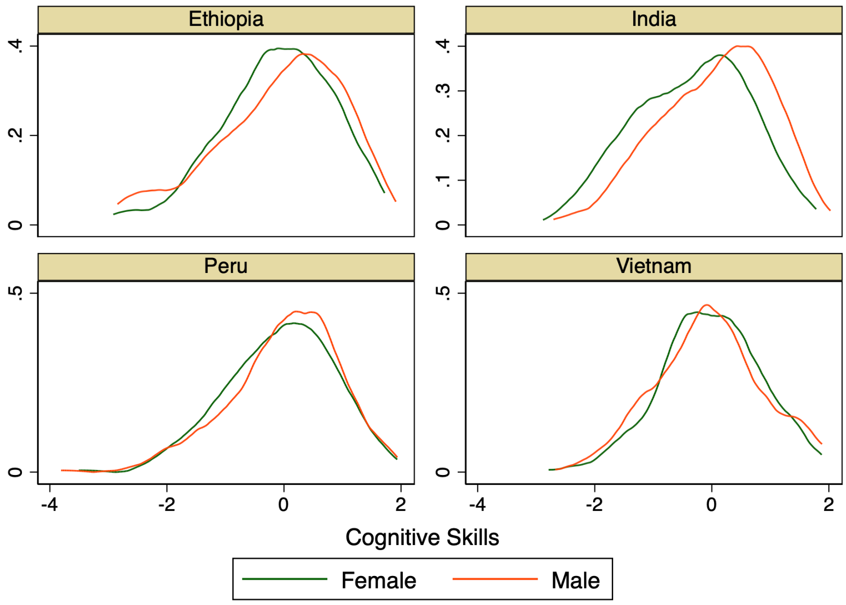
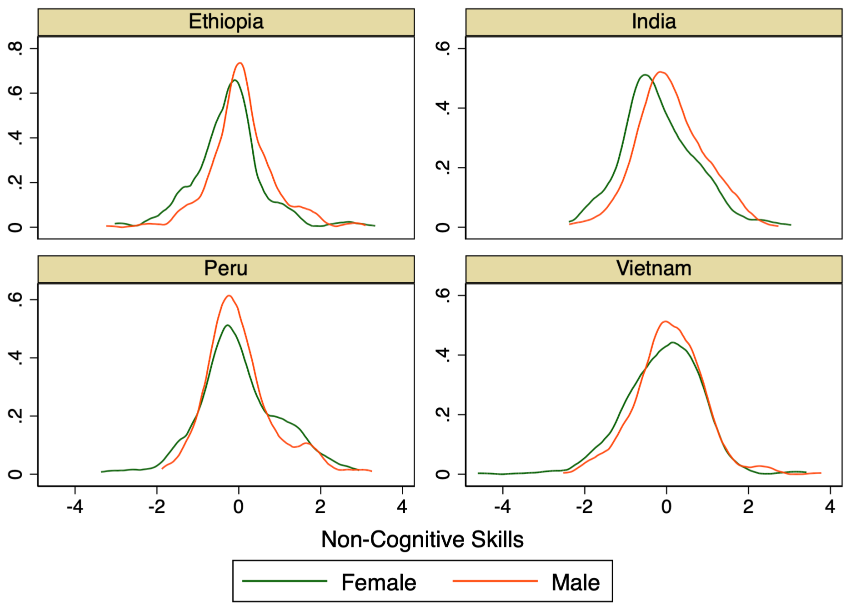


Figure 3: Distribution of latent non-cognitive skills by gender



3 Empirical Specification

For each country and wave, we separately estimate how the gender gap in earnings changes after accounting for human capital differences.

$$Y_{icw} = \beta_0 + \beta_1 \text{Fem}_{ic} + \beta_2 \text{Cog}_{ic} + \beta_3 \text{NonCog}_{ic} + \beta_4 X_{ic} + \mu_c + \epsilon_{icw} \tag{1}$$

For country c, individual i and wave w, Y_{icw} is the net monthly earnings in PPP, Fem_{ic} is an indicator for whether the child is female, Cog_{ic} is the estimated latent cognitive score, NonCog_{ic} is the estimated latent non-cognitive score and X_{ic} is a vector of control variables – the individual's age in months and an indicator of whether they live in an urban or rural area. Note that the Cog_{ic} and NonCog_{ic} variables use skill measures that predate the labour market outcomes. The main specification also controls for cluster fixed effects.

In a second exercise, we test for differential returns to human capital by gender. Specifically, we estimate the following equation:

$$\begin{aligned} Y_{icw} = \beta_0 + \beta_1 \text{Fem}_{ic} + \beta_2 \text{Cog}_{ic} + \beta_3 \text{NonCog}_{ic} + \\ \beta_4 \text{Fem}_{ic} \times \text{Cog}_{ic} + \beta_5 \text{Fem}_{ic} \times \text{NonCog}_{ic} + \beta_6 X_{ic} + \mu_c + \epsilon_{icw} \end{aligned} \tag{2}$$

Lastly, we pool data from three waves to estimate changes in returns in times of economic hardship. We estimate:

$$\begin{aligned} Y_{ic} = \beta_0 + \beta_1 \text{W2}_{ic} + \beta_2 \text{W3}_{ic} + \beta_3 \text{Cog}_{ic} + \beta_4 \text{NonCog}_{ic} + \\ \beta_5 \text{W2}_{ic} \times \text{Cog}_{ic} + \beta_6 \text{W3}_{ic} \times \text{Cog}_{ic} + \\ \beta_7 \text{W3}_{ic} \times \text{NonCog}_{ic} + \beta_8 \text{W3}_{ic} \times \text{NonCog}_{ic} + \beta_9 X_{ic} + \mu_c + \epsilon_{ic} \end{aligned} \tag{3}$$

where $W2_{ic}$ and $W3_{ic}$ are indicators for the second and third wave of the phone survey, using pre-Covid earnings data as the baseline.

We estimate the non-linear exponentiated models by Poisson pseudo maximum likelihood (PPML), as proposed by Santos-Silva & Tenreyro (2006) for the estimation of Mincer equations[9]. This method is well-suited for analysing skewed variables with a non-negligible proportion of zeros, as acknowledged by recent studies investigating earnings data such as Broten et al. (2022) and Powell & Seabury (2018), but also by studies in the trade (e.g. Fally, 2015), aid (e.g. Bommer et al., 2022), and migration (e.g. Adovor et al., 2021) literature.

In our context, a sizable number of observations are zero earners, partly due to the low female labour force participation levels observed in developing countries. As gender differences in employment constitute an important aspect of our analysis, it is essential to use models that appropriately account for zero values. Note that with this type of data, the use of exponential forms such as PPML models require weaker assumptions about the error distribution compared to log-linear estimations (Blackburn, 2007; Santos-Silva & Tenreyro, 2006). Importantly, the exponential model allows us to study the conditional expectation of earnings, rather than the conditional expectation of the log of earnings (Powell & Seabury, 2018). Furthermore, to produce consistent

[9] Note that PPML models can be used even if the data is not Poisson distributed and if the dependent variable is not an integer (Gourieroux et al., 1984).

estimates, PPML models do not require an excludable instrument or non-linearities in the transformation of predicted probabilities, as it is the case in Heckman two-step selection models. We therefore employ PPML models in our analysis. As an alternative, we also present the results using a Heckman two-step selection model in the appendix in Table A17.

Since the main explanatory variables were generated through extraction of latent factors, the inputs in the regression have a sampling distribution of their own. We account for this source of variation by presenting bootstrapped standard errors, clustered at the child level. In our analysis, we substantially reduce measurement error issues by using latent factors as opposed to the raw human capital indicators. Moreover, we can address issues of simultaneity and omitted variable bias, since we observe cognitive, non-cognitive and health measures at least four years prior to the labour market outcomes[10]. Although our estimates do identify causal effects, we describe patterns that have important academic and policy implications[11].

4 Results

4.1 The gender gap and human capital

Changes in gender earnings gap after accounting for human capital

We estimate model 1 using pre-Covid labour market data under three slightly different specifications. The first includes baseline controls, the second adds measures for cognitive and non-cognitive skills and the third adds height-for-age z-scores (HAZ). In Figure 4, we plot the coefficients for the female dummy variable from these models (see Tables A1, A4 and A5 in the appendix). In the baseline specification without human capital measures, the female disadvantage in earnings is economically and statistically significant in all countries. Women in Vietnam and Peru face the lowest penalties in earnings, but this gap is still substantial – women earn approximately 30% less than their male counterparts on average. This disadvantage is larger in Ethiopia, where the estimate grows to more

[10]The absence of the multiple measures of human capital components we observe is usually raised as important concerns in the estimation of returns (Lindqvist and Vestman, 2011; Hanushek et al. 2015). To our knowledge, Danon et al. (2023), Glewwe et al. (2022) and Rosas et al (2017) are the only studies sharing this major advantage in the context of a low-income economy. Note that Lindvist and Vestman (2011) argue that due to the interdependence of human capital dimensions, their simultaneous inclusion produces lower bound estimates, whereas the single inclusion generates the upper bound.

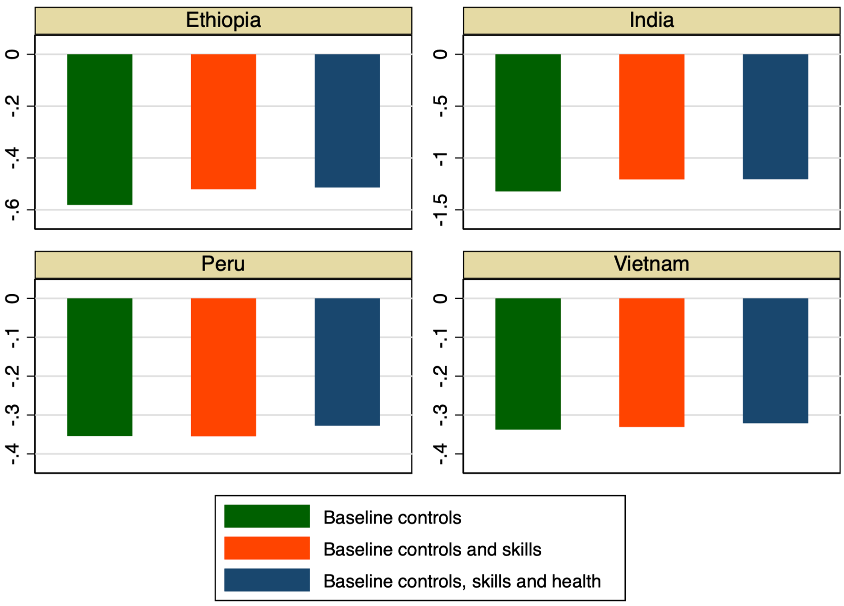
[11]In a further specification, we test for the robustness of our results against the inclusion of a binary indicator for the completion of higher education. Given that all components of human capital are accounted for, it is unclear what schooling stands for in this specification. Previous studies remain rather agnostic and generally point to either measurement error in skills being picked up by schooling or some other channel through which schooling affects labor market outcomes, such as signaling effects (e.g. Glewwe et al., 2022; Edin et al., 2022). It is also plausible that schooling itself is a channel through which human capital affects earnings.

than 44%. India presents the largest disadvantage with a penalty of approximately 73%.[12]

In the case of Ethiopia and India, the gender gap decreases slightly after adjusting for skills and HAZ to 41% and 70% respectively, whereas in Peru and Vietnam, this gap does not appear to change systematically. While the point estimates decrease as expected across the three specifications, we do not observe any large changes in the coefficients. This suggests that the human capital differences we documented above are not able to fully explain the large earnings gaps in any of the four countries.

In our third specification, we observe statistically significant coefficients for cognitive skills across country samples but not for non-cognitive skills or HAZ (see Table A5 in the appendix). For this reason, we will focus on cognitive skills in the next sections.[13]

Figure 4: Pre-covid gender earnings gap



Changes in the earnings gap across cognitive skills levels

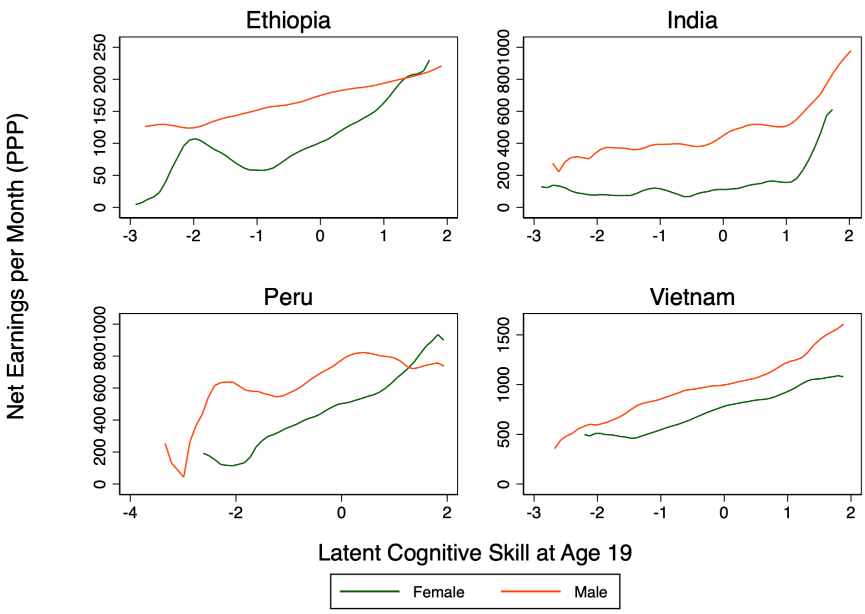
We deepen our exploration of the gender gap in earnings during the pre-Covid period by focusing on the relationship between cognitive skills and earnings. In Figure 5, we plot local polynomial models that regress earnings on cognitive skills for men and women separately, which includes non-earners as well. As expected, we observe that earnings generally increase with higher cognitive skills levels for both men and women in all four

[12]The effect for the binary gender indicator expressed as percentage change in earnings can be calculated as $100x(e^{\beta} - 1)$, where β is the estimated coefficient.

[13]We also investigate the separate impact of cognitive and non-cognitive components on earnings (see Table A2 and A3 in the Appendix). We find that non-cognitive skills have a significant effect on earnings in the absence of cognitive skill measures, suggesting that our non-cognitive scores may partly reflect cognitive skills. This makes intuitive sense given that the two skills are often correlated (Schanzenbach et al. 2016).

countries. An important finding is that female earnings are lower than male earnings at virtually every level of cognition. Interestingly, the gender gap appears to decrease at higher cognitive skill levels in Ethiopia and Peru, suggesting that greater human capital reduces gender inequalities in these labour markets. In the Indian sample, the gap seems to partially close only at very high levels of cognition, whereas the gap in the Vietnamese sample remains similar across all levels of cognitive skills.[14]

Figure 5: Pre-covid earnings across cognitive skill levels



We formalize this exercise by estimating models based on equation 2, which includes an interaction term between the female dummy variable and the skill measures. This allows us to formally test whether the visual patterns observed in Figure 5 reflect statistically significant estimates. In Table 2, we present the regression results for the four country samples[15]. As observed, the interaction term of interest has statistically significant coefficients for the cases of Ethiopia and Peru, confirming our interpretation of the polynomial regression depicted in Figure 5. These effects are also economically significant, since an additional unit of the cognitive skill measure roughly reduces the gender gap in earnings by 50% and 60% for individuals with average cognitive skills in Ethiopia and Peru, respectively. At the same time, it is unclear why we do not observe

[14]See Table A13 for the economic sector of employment by cognition level and gender. The categories considered are agriculture, manufacturing, services, and unemployment. For the first three categories, the ISIC v4. classification is followed (UN, 2008). The service sector has the highest representation of individuals in the male and female samples with high levels of cognition, except for females in India, where unemployment dominates. For males with low levels of cognition, the service sector remains as the category with the largest share, whereas females with low levels of cognition are more likely to be unemployed, with the exception of Peru.

[15]Tables A6 to A12 show estimates for non-cognitive skills for the models of Tables 2 to 7.

similar patterns in the Indian and Vietnamese sample. We will return to this issue in a later section.[16]

Table 2: Effect of gender and skill level on pre-covid earnings

	Ethiopia	India	Peru	Vietnam
Female	-0.579***	-1.221***	-0.406***	-0.341***
	(0.119)	(0.108)	(0.103)	(0.047)
Cognitive Skills	0.069	0.282***	0.097*	0.135***
	(0.068)	(0.058)	(0.058)	(0.039)
Female × Cognitive Skills	0.375***	0.042	0.267**	0.039
	(0.136)	(0.124)	(0.109)	(0.058)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	655	846	441	793

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earning. Bootstrapped standard errors clustered at the child level in parentheses. The model includes the following variables: age in months, urban/rural residence, cluster fixed effects, non-cognitive skills, its interaction with gender and a constant.

4.2 The extensive and intensive margin

The above estimates are based on a pooled sample of both the zero earners and positive earners. Hence, our observed results may be driven by either differences in employment (the extensive margin) or differences in earnings among the employed (the intensive margin). In this section, we investigate these two mechanisms separately. First, we analyse how human capital measures impact the proportion of women in paid employment. Second, we repeat the above analysis in Table 2 for the sub-sample of the employed. We present these results in Tables 3 and 4 respectively.

We find that the results in the previous section are largely explained by the extensive margin. In the Ethiopian and Peruvian samples, the gender gap in employment decreases by more than two thirds with an increasing unit of cognitive skills. Hence, women with lower cognitive skills are much less likely to work for pay than their male counterparts. For the Vietnamese sample, the gap seems to also decrease with higher skills, although the magnitude of this effect, while significant, is somewhat smaller. The gender gap in employment in India is the largest, and this gap is unaffected by skill levels.

Interestingly, the employment status of men does not systematically relate to cognitive skill levels. However, their earnings conditional on employment increase with greater cognitive skills. In all four countries, the gender gap at the intensive margin does not significantly close even at higher cognitive skill levels. The results in Table 3 and 4 are

[16]Our results are robust to controlling for years of education, work experience and HAZ, and including the top 1% earners, as shown in Tables A19 -A22.

corroborated by the two-step Heckman selection model and OLS respectively in tables A17 A18 in the appendix.

Table 3: Effect of gender and skill level on pre-covid employment

	Ethiopia	India	Peru	Vietnam
Female	-0.187***	-0.398***	-0.182***	-0.144***
	(0.035)	(0.032)	(0.040)	(0.025)
Cognitive Skills	-0.032	0.008	-0.039	0.013
	(0.025)	(0.027)	(0.030)	(0.016)
Female × Cognitive Skills	0.112***	-0.008	0.163***	0.048*
	(0.038)	(0.035)	(0.049)	(0.028)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	671	856	452	818

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. LPM estimates. The dependent variable is paid employment status. Bootstrapped standard errors clustered at the child level in parentheses. The model includes the following variables: age in months, urban/rural residence, cluster fixed effects, non-cognitive skills, its interaction with gender and a constant.

Table 4: Effect of gender and skill level on pre-covid earnings for sub-sample of employed

	Ethiopia	India	Peru	Vietnam
Female	-0.243**	-0.414***	-0.150**	-0.181***
	(0.097)	(0.078)	(0.075)	(0.042)
Cognitive Skills	0.129***	0.269***	0.147***	0.126***
	(0.043)	(0.053)	(0.047)	(0.040)
Female × Cognitive Skills	0.074	0.052	0.025	-0.029
	(0.108)	(0.087)	(0.087)	(0.054)
Bootstrap N	5,265	5,265	5,265	5,265
Effective N	350	430	350	695

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is conditional earnings. Bootstrapped standard errors clustered at the child level in parentheses. The model includes the following variables: age in months, urban/rural residence, cluster fixed effects, non-cognitive skills, its interaction with gender and a constant.

In summary, we demonstrate that the overall gender earnings gap partly closes as cognitive skills increase in Ethiopia and Peru, but remains unchanged across cognition levels in India and Vietnam. In Ethiopia, Peru and Vietnam, higher skilled women are more likely to be earning (extensive margin). Conditional on being in paid work, note that the return to skills are not significantly lower for women who are working, however, for every level of skill, the gender gap in earnings remains constant, being largest in India and smallest in Peru.

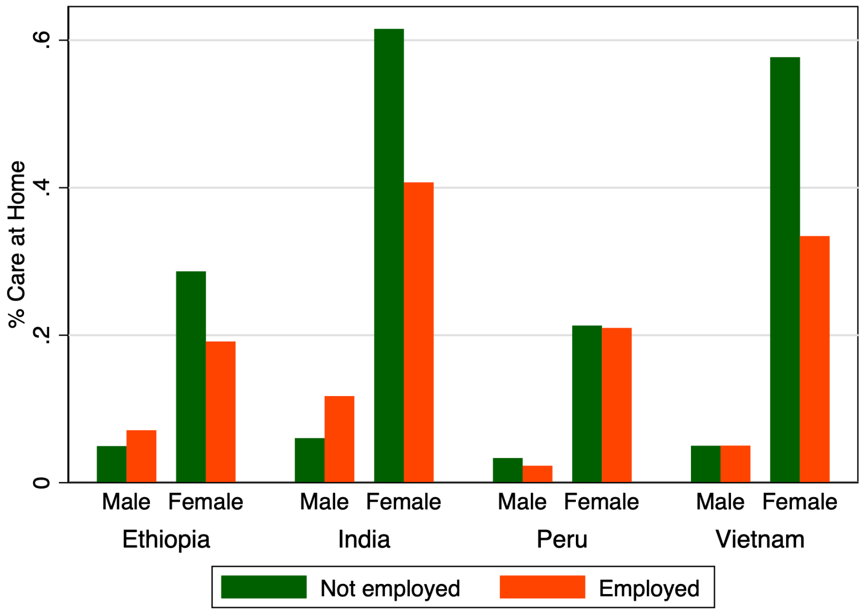
To investigate this, we document selection into economic sectors, categorised into agriculture, manufacturing, and services. The share of employment is lowest for agriculture, followed by manufacturing, while services have the highest share. The share of women in agriculture is very low in all countries, and particularly low for higher-skilled women (see Table A13 in the Appendix). In all countries, women are more likely to work in the service sector if they have higher skills. In Ethiopia and Peru, the likelihood of working in services is systematically higher for women compared to men. When we add controls for working in different sectors, we find that the unexplained gender gap does reduce significantly in all four countries. Hence, it seems likely that selection into lower-paid jobs in the services sector contributes to the lower earnings of women across the distribution of skills.

4.3 The role of social norms

Next, we investigate unpaid care work and attitudes towards gender roles as potential explanations for the cross-country variations. We hypothesize that in samples where women face a high burden of unpaid care work, higher levels of cognitive skills may not translate into lower gender gaps in labour market outcomes, through either reduced participation, or fewer hours worked. The gender gap may also persist in societies with poorer attitudes towards women's employment, education, and social status.

In Figure 6, we depict the proportion of men and women who perform care work at home by employment status. Women perform substantially more care work than men in all countries. Among women, those who are employed are less likely to perform care work. It is unclear whether other female household members take over these duties for this group, whether the higher skills and positive earnings lead these households to outsource this type of work or whether the households these women live in have lower care needs in the first place. Importantly, the proportion of women performing care work is highest in the same countries where higher cognitive skills do not close the earnings gap, namely India and Vietnam. Moreover, these two countries have the largest gender gap in care work, further corroborating the country-specific patterns observed in the previous sections.

Figure 6: Care work by gender and employment status



In Table 5, we repeat our previous analysis but include an indicator of whether the individual performs care work at home. As expected, the coefficient for this variable is negative, large, and statistically significant in India and Vietnam, but not in Ethiopia or Peru. This suggests that the presence of large gender gaps in care work responsibilities may hinder the role of cognitive skills in closing the gap in labor market outcomes.

In the appendix in Table A16, we repeat this exercise using the Attitudes toward Women Scale for Adolescents index (AWSA), which represents the attitudes towards the role of women in society touching aspects of employment, education and social status. The patterns in these estimates are less clear, which might be arguably expected given that the concept this index attempts at measuring is much broader, with some components having a rather indirect relation to employment and earnings.

Table 5: Effect of gender and skill level on pre-covid earnings, controlling for carework

	Ethiopia	India	Peru	Vietnam
Female	-0.562***	-0.989***	-0.434***	-0.269***
	(0.123)	(0.112)	(0.103)	(0.050)
Cognitive Skills	0.067	0.261***	0.100*	0.136***
	(0.068)	(0.057)	(0.058)	(0.039)
Female × Cognitive Skills	0.373***	0.001	0.272**	0.021
	(0.136)	(0.119)	(0.109)	(0.057)
Performed Carework	-0.108	-0.650***	0.167	-0.239***
	(0.170)	(0.128)	(0.211)	(0.072)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	655	843	441	792

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is conditional earning. Bootstrapped standard errors clustered at the child level in parentheses. The model includes the following variables: age in months, urban/rural residence, cluster fixed effects, non-cognitive skills, its interaction with gender and a constant.

Given the role of care work in our estimates, understanding its variation might be complementary to our findings. While a systematic analysis is beyond the scope of this paper, we briefly postulate potential determinants. There are several factors that could explain the cross-country and within-country variation in care work among women depicted in Figure 6.[17] For instance, some women might simply live in households in lesser need of care work. This would be the case in the absence of marriage or young children. Higher skilled women may delay fertility given the higher opportunity cost of not working, and also due to higher bargaining power within the household.

As suggested by Figures A2 and A3, (employed) women in the Ethiopian sample are the least likely group to be married or have young children, which might contribute to their comparatively low levels of care work. Another possibility is that for a given level of care need, women might outsource this type of work to another family member, care worker or pre-school institution. This type of outsourcing is arguably more accessible in urban areas, which is in line with the high levels of urban status among women in the Peruvian and Ethiopian sample (see Figure A4).

4.4 Returns to skills during the COVID-19 Crisis

In the previous section, we focused on earnings during the pre-pandemic period between December 2019-February 2020. In this section, we extend our analysis to two additional periods during the crisis – Wave 2 in August-October 2020 and Wave 3 in

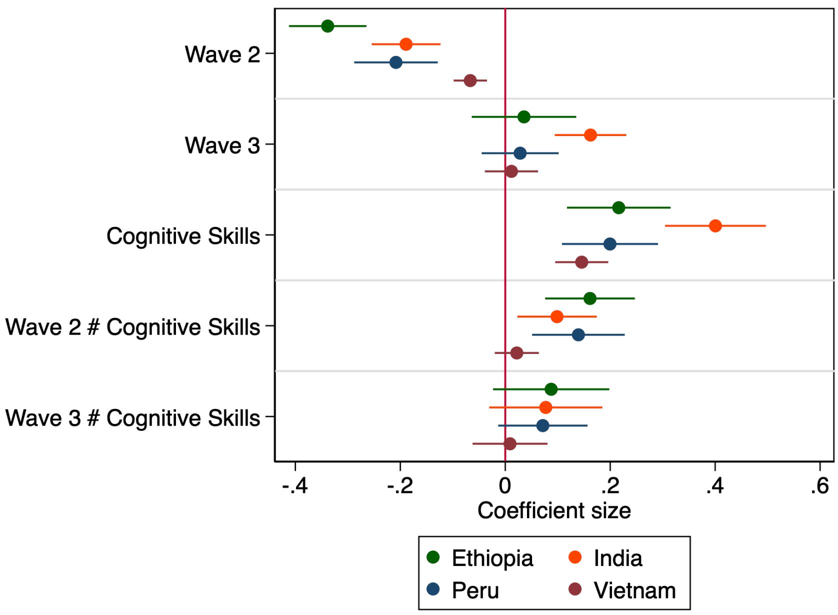
[17]Recall that since YL is a cohort study, the women are all born within a 12 month window, so life-cycle effects are not driving the results.

October-December 2021. These periods were characterized by unprecedented mobility restrictions and global economic distress due to the pandemic. Hence, we would expect such an environment to impact labour market outcomes and the allocation of care work in our countries of study.

As specified in equation 3, we pool the labour market data from the three time periods and regress earnings on baseline controls, human capital variables, period dummies, and interactions between human capital and the period dummies. We present the regression coefficients in Figure 7 (see the corresponding Table A14 for additional coefficients). As expected, earnings decreased between Wave 1 and Wave 2 in all countries. Vietnam faced the least drop in earnings of the four countries, potentially because the impact of the pandemic was not as severe during this period (see Figure A1 in the Appendix).

In Wave 3, earnings returned to pre-pandemic levels in Ethiopia, Peru, and Vietnam, and even increased in India. The observed trends in Wave 3 may have been a result of the lifting of mobility restrictions, but we cannot rule out the role of country or region-specific seasonalities in economic activity.[18]

Figure 7: Coefficient sizes for regression of earnings on skills levels across three waves



We further explore how returns to cognitive skills of women and the gender gap varied during Wave 2 (Table 6), when the COVID crisis was at its peak in most countries, and in Wave 3 (Table 7) when the economic environment improved and contrast these estimates to those in Table 2. To better compare the gender gaps and returns to cognitive skills across time periods, we limit the sample to those individuals with non-missing data in all three waves.

[18]The returns to cognitive skills increased in the three countries with economic distress, suggesting a resilience benefit of human capital during economic hardship.

In Wave 2, the gender gap for individuals with average cognitive skills increased in the samples of Ethiopia, Peru and Vietnam, while it decreased in India. In Wave 3, the gap increased in India and Peru, while it remained relatively similar in Ethiopia and Vietnam. In Ethiopia and Peru, women experienced greater returns to cognitive skills in both Wave 2 and Wave 3. Recall that these are the two country samples with greater returns to skills for women in the pre-covid period. In Wave 2, the differences in returns by gender is amplified in both countries, suggesting that the effect of higher cognitive skills on the gender gap is strengthened in the context of economic distress. In Wave 3, this amplification further increases in Peru, while it goes back to pre-covid levels in Ethiopia. In India and Vietnam, the returns to skills remain relatively unchanged during this period.

Table 6: Effect of gender and skills on earnings during Wave 2

	Ethiopia	India	Peru	Vietnam
Female	-0.746***	-1.056***	-0.702***	-0.378***
	(0.172)	(0.124)	(0.127)	(0.057)
Cognitive Skills	0.253***	0.418***	0.197***	0.127**
	(0.098)	(0.072)	(0.070)	(0.050)
Female × Cognitive Skills	0.579***	-0.052	0.320*	0.069
	(0.175)	(0.134)	(0.169)	(0.069)
Bootstrap N	7,146	7,146	7,146	7,146
Effective N	460	812	394	716

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earning. Bootstrapped standard errors clustered at the child level in parentheses. The model includes the following variables: age in months, urban/rural residence, cluster fixed effects, non-cognitive skills, its interaction with gender and a constant.

Table 7: Effect of gender and skill on earnings during Wave 3

	Ethiopia	India	Peru	Vietnam
Female	-0.603***	-1.366***	-0.699***	-0.358***
	(0.150)	(0.111)	(0.111)	(0.061)
Cognitive Skills	0.207**	0.331***	0.071	0.183***
	(0.090)	(0.050)	(0.051)	(0.045)
Female × Cognitive Skills	0.473***	0.086	0.445***	-0.029
	(0.156)	(0.123)	(0.122)	(0.068)
Bootstrap N	7,146	7,146	7,146	7,146
Effective N	460	812	394	716

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earning. Bootstrapped standard errors clustered at the child level in parentheses. The model includes the following variables: age in months, urban/rural residence, cluster fixed effects, non-cognitive skills, its interaction with gender and a constant.

5 Conclusion

In this paper, we construct latent factors of cognitive and non-cognitive skills in mid-adolescence using high quality measures of human capital. We use these measures to investigate the role of human capital in the gender gap in labour market outcomes in four developing countries. Our results indicate that cognitive skills are predictive of labour market outcomes, whereas non-cognitive measures are not. In all study countries but India, women have the same level of cognitive skills as men. Yet all countries show a substantial gender gap in labour market outcomes. In the special case of India, where women in our sample show lower levels of cognitive skills, much of the gender gap in earnings remains unexplained even after accounting for carefully constructed human capital indicators. For this reason, simply closing gender gaps in human capital might be insufficient for policies that aim at closing labour market gaps.

At the same time, we find that higher cognitive skills are associated with lower gender gaps in earnings in two out of the four country samples, namely Ethiopia and Peru. This might be the result of higher cognitive skills improving women's bargaining power both in the household and in the labour market. Labour markets that transition towards an employment structure that demands higher cognitive skills might therefore have benefits not only in terms of economic growth but also in terms of gender equality in labour markets, if occurring in tandem with a promotion of cognitive skills development for women as well. Importantly, the measures we use to construct cognitive skills might encompass the test-takers effort or other higher-order skills, as these have been shown to affect performance in cognitive tests (Gneezi et al., 2019; Segal, 2013; Cunha & Heckman, 2007). Understanding to what extent the policy implications of these findings might also involve the promotion of higher-order skills calls for further research.

The reduction of the earnings gap as cognitive skills increase is a pattern that we do not find in country samples where the likelihood of doing care work is particularly present for women. In India and Vietnam, the gender gap persists even as cognitive skills increase. Our analysis hints at these labour market inequalities being driven by the unequal burden of care work. While we would expect gender inequalities to dissipate with greater cognitive skills, we find that care work crucially affects youth's earnings. Thus, while a higher level of cognitive skills seems to be a force of gender convergence, rigidity regarding care work has the capacity to block this dynamic. To this effect, interventions that improve access to childcare (Evans et al., 2021) or shift gender social norms through school- and university-based interventions may be equally relevant (Dhar et al. 2022; Porter & Serra 2021). Importantly, while raising cognitive skills of women, improving access to childcare and shifting gender social norms are all relevant aspects independently from one another, tackling each of these issues in isolation might not be effective at closing gender gaps in labour markets. Our analysis points to this being the case for cognitive skills in half of the study countries, whereas Nandi et al (2020) finds evidence for access to childcare alone not being sufficient for a systematic improvement in India.

In our analysis, we focus on the labour market outcomes of the youth. However, the dynamics between human capital and earnings may alter as these young workers acquire additional labour market experience. On one hand, the returns to human capital may increase over time as the skill sets of workers become more observable. Previous studies based in developed countries have shown that lifetime returns are often underestimated in the case of recent labour market entrants, since the skills premia often grows steeper after early career years (Lin et al. 2018; Nybom, 2017; Hanushek et al. 2015). Hence, we might expect the gender gap to decrease with time. On the other hand, the women in our sample may eventually have more children, and so the burden of childcare may exacerbate and negatively impact their labour market outcomes (Cools et al. 2017). Further research should explore how these and other developments in the lives of young workers influence the relationship between the gender gap and human capital over time.

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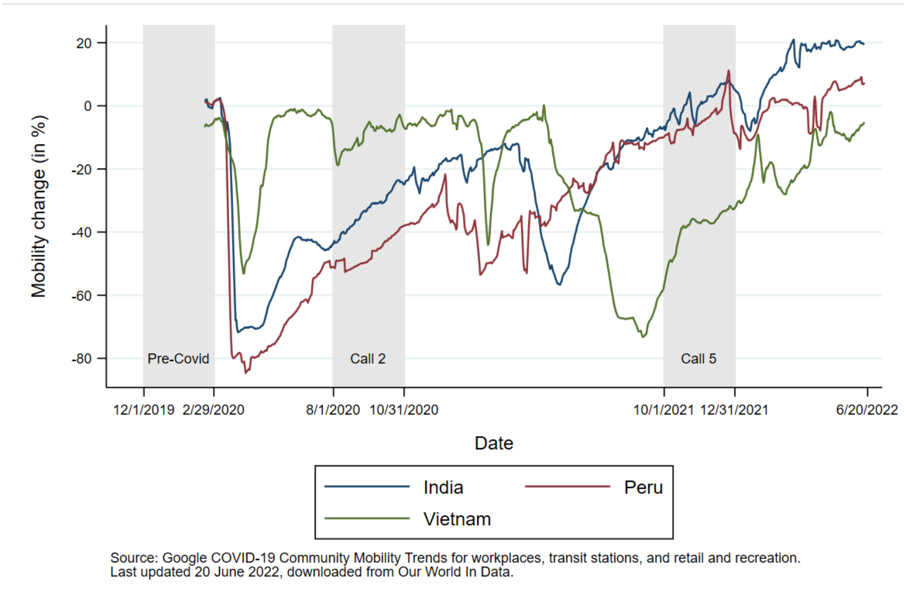
7 Appendix

7.1 Additional Figures & Extended Tables

Figure A1: Covid-19 community mobility trends in young lives countries



Full regression tables for Figure 4

Table A1: Earning gap by gender with baseline control

	Ethiopia	India	Peru	Vietnam
Female	-0.581***	-1.322***	-0.354***	-0.338***
	(0.109)	(0.106)	(0.103)	(0.044)
Urban	0.632***	0.467***	0.345**	0.405***
	(0.142)	(0.124)	(0.134)	(0.059)
Age in months, Wave 1	-0.005	-0.018	0.000	0.008
	(0.015)	(0.012)	(0.011)	(0.007)
Constant	6.478	11.920***	6.143*	4.036*
	(4.754)	(3.692)	(3.596)	(2.202)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	655	846	441	793

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earnings. Cluster fixed effects included. Bootstrapped standard errors clustered at the child level in parentheses.

Table A2: Earnings gap by gender with baseline control and only cognitive skills

	Ethiopia	India	Peru	Vietnam
Female	-0.546***	-1.209***	-0.348***	-0.337***
	(0.111)	(0.111)	(0.099)	(0.044)
Cognitive Skills	0.193***	0.300***	0.211***	0.158***
	(0.058)	(0.056)	(0.048)	(0.029)
Urban	0.597***	0.395***	0.240*	0.319***
	(0.143)	(0.125)	(0.133)	(0.058)
Age in months, Wave 1	-0.003	-0.019*	0.002	0.009
	(0.015)	(0.011)	(0.011)	(0.007)
Constant	5.655	11.971***	5.754	3.963*
	(4.653)	(3.510)	(3.591)	(2.176)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	655	846	441	793

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earnings. Cluster fixed effects included. Bootstrapped standard errors clustered at the child level in parentheses.

Table A3: Earnings gap by gender with baseline control and only non-cognitive skills

	Ethiopia	India	Peru	Vietnam
Female	-0.540***	-1.292***	-0.363***	-0.327***
	(0.113)	(0.109)	(0.101)	(0.045)
Non-Cognitive Skills	0.135**	0.107*	0.138***	0.063**
	(0.058)	(0.061)	(0.050)	(0.028)
Urban	0.632***	0.458***	0.352***	0.392***
	(0.141)	(0.125)	(0.133)	(0.058)
Age in months, Wave 1	-0.005	-0.019*	0.001	0.008
	(0.015)	(0.012)	(0.011)	(0.007)
Constant	6.535	12.101***	5.970*	4.232*
	(4.724)	(3.640)	(3.488)	(2.194)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	655	846	441	793

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earnings. Cluster fixed effects included. Bootstrapped standard errors clustered at the child level in parentheses.

Table A4: Earnings gap by gender with baseline controls, cognitive and non-cognitive skills

	Ethiopia	India	Peru	Vietnam
Female	-0.520***	-1.207***	-0.355***	-0.331***
	(0.115)	(0.113)	(0.099)	(0.045)
Cognitive Skills	0.173***	0.295***	0.188***	0.150***
	(0.062)	(0.053)	(0.053)	(0.029)
Non-Cognitive Skills	0.096	0.018	0.102*	0.039
	(0.061)	(0.059)	(0.053)	(0.028)
Urban	0.601***	0.395***	0.258*	0.316***
	(0.142)	(0.126)	(0.133)	(0.057)
Age in months, Wave 1	-0.003	-0.019*	0.002	0.008
	(0.015)	(0.011)	(0.011)	(0.007)
Constant	5.817	11.994***	5.636	4.105*
	(4.633)	(3.521)	(3.533)	(2.184)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	655	846	441	793

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earnings. Cluster fixed effects included. Bootstrapped standard errors clustered at the child level in parentheses.

Table A5: Earnings gap by gender with baseline control, skills and health

	Ethiopia	India	Peru	Vietnam
Female	-0.514***	-1.204***	-0.327***	-0.321***
	(0.118)	(0.113)	(0.099)	(0.045)
Cognitive Skills	0.172***	0.281***	0.170***	0.149***
	(0.062)	(0.053)	(0.054)	(0.028)
Non-Cognitive Skills	0.095	0.017	0.108**	0.034
	(0.061)	(0.059)	(0.053)	(0.029)
Height-for-age z-score	-0.017	0.076*	0.072	0.035
	(0.041)	(0.039)	(0.044)	(0.031)
Urban	0.586***	0.400***	0.298**	0.319***
	(0.143)	(0.128)	(0.136)	(0.057)
Age in months, Wave 1	-0.003	-0.020*	0.001	0.008
	(0.015)	(0.011)	(0.011)	(0.007)
Constant	5.581	12.365***	6.046*	4.190*
	(4.649)	(3.534)	(3.623)	(2.298)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	650	842	434	780

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earnings. Cluster fixed effects included. Bootstrapped standard errors clustered at the child level in parentheses.

Tables reporting non-cognitive skills estimates for Tables 2 - 7

Table A6: Effect of gender and skill level on pre-covid earnings

	Ethiopia	India	Peru	Vietnam
Female	-0.579***	-1.221***	-0.406***	-0.341***
	(0.119)	(0.108)	(0.103)	(0.047)
Non-Cognitive Skills	0.021	-0.042	0.107*	0.022
	(0.078)	(0.066)	(0.057)	(0.034)
Female × Non-Cognitive Skills	0.192	0.202	-0.021	0.035
	(0.121)	(0.142)	(0.104)	(0.056)
Cognitive Skills	0.069	0.282***	0.097*	0.135***
	(0.068)	(0.058)	(0.058)	(0.039)
Female × Cognitive Skills	0.375***	0.042	0.267**	0.039
	(0.136)	(0.124)	(0.109)	(0.058)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	655	846	441	793

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earnings. Bootstrapped standard errors clustered at the child level in parentheses. Includes the following controls: age in months, urban/rural residence, cluster fixed effects and a constant.

Table A7: Effect of gender and skill level on pre-covid employment

	Ethiopia	India	Peru	Vietnam
Female	-0.370***	-0.805***	-0.258***	-0.165***
	(0.074)	(0.080)	(0.060)	(0.030)
Non-Cognitive Skills	0.049	-0.057	0.061**	0.008
	(0.058)	(0.047)	(0.031)	(0.014)
Female × Non-Cognitive Skills	0.016	0.098	0.043	-0.018
	(0.092)	(0.099)	(0.053)	(0.034)
Cognitive Skills	-0.066	0.021	-0.048	0.013
	(0.047)	(0.040)	(0.036)	(0.017)
Female × Cognitive Skills	0.279***	-0.029	0.237***	0.062*
	(0.088)	(0.082)	(0.068)	(0.034)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	671	856	452	818

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is employment status. Bootstrapped standard errors clustered at the child level in parentheses. Includes the following controls: age in months, urban/rural residence, cluster fixed effects and a constant.

Table A8: Effect of gender and skill level on pre-covid earnings for sub-sample of employed

	Ethiopia	India	Peru	Vietnam
Female	-0.243**	-0.414***	-0.150**	-0.181***
	(0.097)	(0.078)	(0.075)	(0.042)
Non-Cognitive Skills	-0.065	0.014	0.042	0.016
	(0.045)	(0.054)	(0.056)	(0.039)
Female × Non-Cognitive Skills	0.296***	0.078	-0.055	0.052
	(0.110)	(0.099)	(0.085)	(0.056)
Cognitive Skills	0.129***	0.269***	0.147***	0.126***
	(0.043)	(0.053)	(0.047)	(0.040)
Female × Cognitive Skills	0.074	0.052	0.025	-0.029
	(0.108)	(0.087)	(0.087)	(0.054)
Bootstrap N	5,265	5,265	5,265	5,265
Effective N	350	430	350	695

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is conditional earnings. Bootstrapped standard errors clustered at the child level in parentheses. Includes the following controls: age in months, urban/rural residence, cluster fixed effects and a constant.

Table A9: Effect of gender and skill level on pre-covid earnings, controlling for carework

	Ethiopia	India	Peru	Vietnam
Female	-0.562***	-0.989***	-0.434***	-0.269***
	(0.123)	(0.112)	(0.103)	(0.050)
Non-Cognitive Skills	0.025	-0.042	0.105*	0.027
	(0.079)	(0.066)	(0.057)	(0.034)
Female × Non-Cognitive Skills	0.181	0.168	-0.007	0.035
	(0.123)	(0.143)	(0.105)	(0.056)
Cognitive Skills	0.067	0.261***	0.100*	0.136***
	(0.068)	(0.057)	(0.058)	(0.039)
Female × Cognitive Skills	0.373***	0.001	0.272**	0.021
	(0.136)	(0.119)	(0.109)	(0.057)
Performed Carework	-0.108	-0.650***	0.167	-0.239***
	(0.170)	(0.128)	(0.211)	(0.072)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	655	843	441	792

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is conditional earning. Bootstrapped standard errors clustered at the child level in parentheses. The model includes the following variables: age in months, urban/rural residence, cluster fixed effects and a constant.

Table A10: Effect of gender and skills on earnings during Wave 1

	Ethiopia	India	Peru	Vietnam
Female	-0.545***	-1.149***	-0.467***	-0.350***
	(0.149)	(0.106)	(0.091)	(0.052)
Non-Cognitive Skills	0.036	-0.019	0.108	0.054
	(0.082)	(0.071)	(0.073)	(0.037)
Female × Non-Cognitive Skills	0.222	0.187	0.042	0.008
	(0.143)	(0.154)	(0.112)	(0.055)
Cognitive Skills	0.043	0.282***	0.070	0.108**
	(0.073)	(0.060)	(0.050)	(0.042)
Female × Cognitive Skills	0.488***	0.079	0.205**	0.056
	(0.139)	(0.122)	(0.090)	(0.065)
Bootstrap N	7,146	7,146	7,146	7,146
Effective N	460	812	394	716

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earnings. Bootstrapped standard errors clustered at the child level in parentheses. Includes the following controls: age in months, urban/rural residence, cluster fixed effects and a constant.

Table A11: Effect of gender and skills on earnings during Wave 2

	Ethiopia	India	Peru	Vietnam
Female	-0.746***	-1.056***	-0.702***	-0.378***
	(0.172)	(0.124)	(0.127)	(0.057)
Non-Cognitive Skills	0.003	-0.062	0.027	0.061
	(0.130)	(0.079)	(0.091)	(0.043)
Female × Non-Cognitive Skills	0.338	0.220	0.014	-0.005
	(0.213)	(0.181)	(0.148)	(0.066)
Cognitive Skills	0.253***	0.418***	0.197***	0.127**
	(0.098)	(0.072)	(0.070)	(0.050)
Female × Cognitive Skills	0.579***	-0.052	0.320*	0.069
	(0.175)	(0.134)	(0.169)	(0.069)
Bootstrap N	7,146	7,146	7,146	7,146
Effective N	460	812	394	716

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earnings. Bootstrapped standard errors clustered at the child level in parentheses. Includes the following controls: age in months, urban/rural residence, cluster fixed effects and a constant.

Table A12: Effect of gender and skills on earnings during Wave 3

	Ethiopia	India	Peru	Vietnam
Female	-0.603***	-1.366***	-0.699***	-0.358***
	(0.150)	(0.111)	(0.111)	(0.061)
Non-Cognitive Skills	0.139	0.004	0.032	0.054
	(0.089)	(0.066)	(0.068)	(0.047)
Female × Non-Cognitive Skills	0.000	0.181	0.137	-0.016
	(0.151)	(0.146)	(0.128)	(0.070)
Cognitive Skills	0.207**	0.331***	0.071	0.183***
	(0.090)	(0.050)	(0.051)	(0.045)
Female × Cognitive Skills	0.473***	0.086	0.445***	-0.029
	(0.156)	(0.123)	(0.122)	(0.068)
Bootstrap N	7,146	7,146	7,146	7,146
Effective N	460	812	394	716

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earnings. Bootstrapped standard errors clustered at the child level in parentheses. Includes the following controls: age in months, urban/rural residence, cluster fixed effects and a constant.

Table reporting shares of employment by economic sector, cognition level and gender

Table A13: Employment in economic sectors by cognition level and gender

Country	Male		Total	Female		Total
	Low Cognition	High Cognition		Low Cognition	High Cognition	
Ethiopia						
Not employed	21.08%	21.39%	42.47%	35.27%	24.36%	59.64%
Agriculture	3.01%	1.20%	4.22%	0.73%	0.73%	1.45%
Manufacturing	5.72%	10.24%	15.96%	5.09%	1.82%	6.91%
Services	16.57%	20.78%	37.35%	12.73%	19.27%	32.00%
Total	46.39%	53.61%	100.00%	53.82%	46.18%	100.00%
India						
Not employed	11.69%	17.41%	29.10%	40.90%	29.79%	70.69%
Agriculture	7.21%	1.99%	9.20%	7.57%	1.18%	8.75%
Manufacturing	10.95%	7.46%	18.41%	5.20%	0.47%	5.67%
Services	15.17%	28.11%	43.28%	5.67%	9.22%	14.89%
Total	45.02%	54.98%	100.00%	59.34%	40.66%	100.00%
Peru						
Not employed	5.67%	6.48%	12.15%	19.61%	10.29%	29.90%
Agriculture	6.48%	4.05%	10.53%	2.94%	0.49%	3.43%
Manufacturing	8.91%	13.77%	22.67%	2.45%	6.86%	9.31%
Services	23.48%	31.17%	54.66%	21.57%	35.78%	57.35%
Total	44.53%	55.47%	100.00%	46.57%	53.43%	100.00%
Vietnam						
Not employed	3.27%	1.76%	5.04%	12.29%	6.51%	18.80%
Agriculture	11.34%	3.53%	14.86%	4.58%	1.20%	5.78%
Manufacturing	16.88%	11.84%	28.72%	13.49%	9.88%	23.37%
Services	20.40%	30.98%	51.39%	20.48%	31.57%	52.05%
Total	51.89%	48.11%	100.00%	50.84%	49.16%	100.00%

Regression table for Figure 7

Table A14: Earnings gap by skill across three rounds

	Ethiopia	India	Peru	Vietnam
Wave 2	-0.338***	-0.189***	-0.208***	-0.067***
	(0.047)	(0.038)	(0.047)	(0.022)
Wave 3	0.036	0.163***	0.028	0.012
	(0.067)	(0.040)	(0.044)	(0.033)
Non-Cognitive Skills	0.137**	0.063	0.090*	0.054*
	(0.059)	(0.055)	(0.052)	(0.029)
Wave 2 × Non-Cognitive Skills	-0.005	0.012	-0.044	0.009
	(0.045)	(0.047)	(0.059)	(0.021)
Wave 3 × Non-Cognitive Skills	0.038	0.023	0.006	0.017
	(0.063)	(0.045)	(0.057)	(0.030)
Cognitive Skills	0.216***	0.401***	0.200***	0.146***
	(0.063)	(0.055)	(0.052)	(0.033)
Wave 2 × Cognitive Skills	0.162***	0.099**	0.139**	0.022
	(0.052)	(0.047)	(0.060)	(0.023)
Wave 3 × Cognitive Skills	0.087	0.077	0.072	0.009
	(0.059)	(0.061)	(0.051)	(0.038)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	1,786	2,516	1,291	2,329

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earnings. Bootstrapped standard errors clustered at the child level in parentheses. Includes the following controls: age in months, urban/rural residence, cluster fixed effects and a constant.

7.2 Additional Tables & Figures on Social Norms

Table A15: Effect of gender and skill interactions on working in services in Wave 1 (includes zero earners)

	Ethiopia	India	Peru	Vietnam
Female	-0.076*	-0.248***	0.014	0.011
	(0.039)	(0.034)	(0.048)	(0.030)
Non-Cognitive Skills	0.039	0.004	0.024	0.015
	(0.031)	(0.031)	(0.042)	(0.030)
Female × Non-Cognitive Skills	-0.030	0.015	0.017	0.018
	(0.039)	(0.036)	(0.061)	(0.041)
Cognitive Skills	-0.014	0.099***	-0.042	0.082***
	(0.023)	(0.024)	(0.035)	(0.025)
Female × Cognitive Skills	0.082**	-0.035	0.169***	0.032
	(0.034)	(0.031)	(0.049)	(0.040)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	607	825	451	812

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. LPM estimates. The dependent variable is working in services. Bootstrapped standard errors clustered at the child level in parentheses. Includes the following controls: age in months, urban/rural residence, and a constant.

Table A16: Effect of gender and skill level on pre-covid earnings, controlling for AWSA

	Ethiopia	India	Peru	Vietnam
Female	-0.571***	-1.325***	-0.446***	-0.358***
	(0.133)	(0.114)	(0.101)	(0.046)
Non-Cognitive Skills	0.021	-0.047	0.079	0.019
	(0.076)	(0.068)	(0.057)	(0.034)
Female × Non-Cognitive Skills	0.172	0.210	-0.035	0.036
	(0.122)	(0.143)	(0.102)	(0.056)
Cognitive Skills	0.059	0.252***	0.035	0.137***
	(0.073)	(0.058)	(0.068)	(0.040)
Female × Cognitive Skills	0.321**	0.028	0.268**	0.031
	(0.132)	(0.125)	(0.111)	(0.060)
AWSA Index (2016)	0.087	0.277**	0.247**	0.015
	(0.120)	(0.118)	(0.107)	(0.053)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	603	840	435	776

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is conditional earning. Bootstrapped standard errors clustered at the child level in parentheses. The model includes the following variables: age in months, urban/rural residence, cluster fixed effects and a constant.

Figure A2: Marital status by gender and employment status

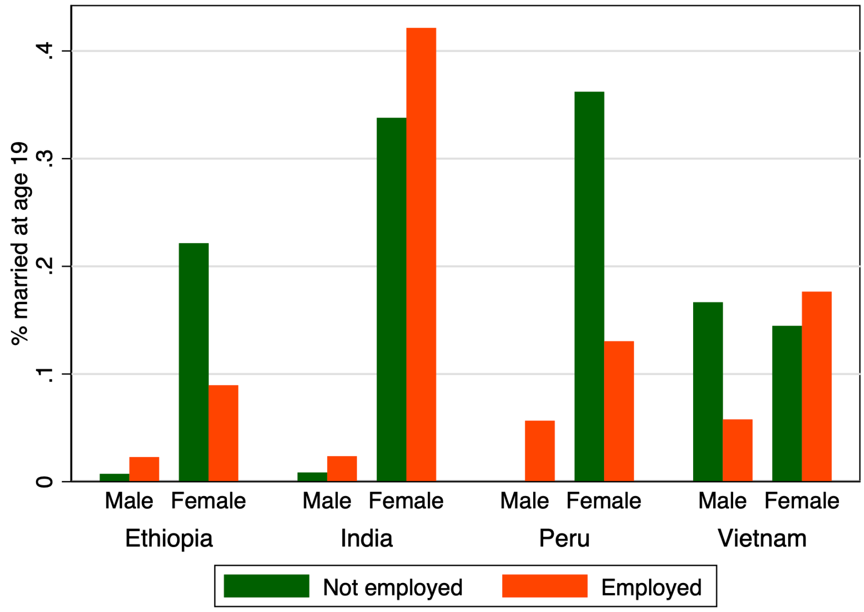


Figure A3: Share with young children by gender and employment status

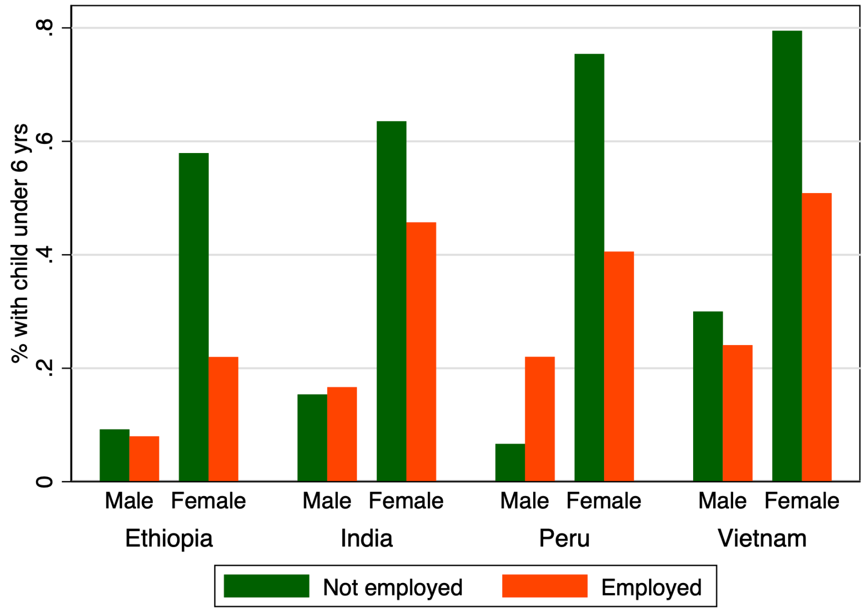
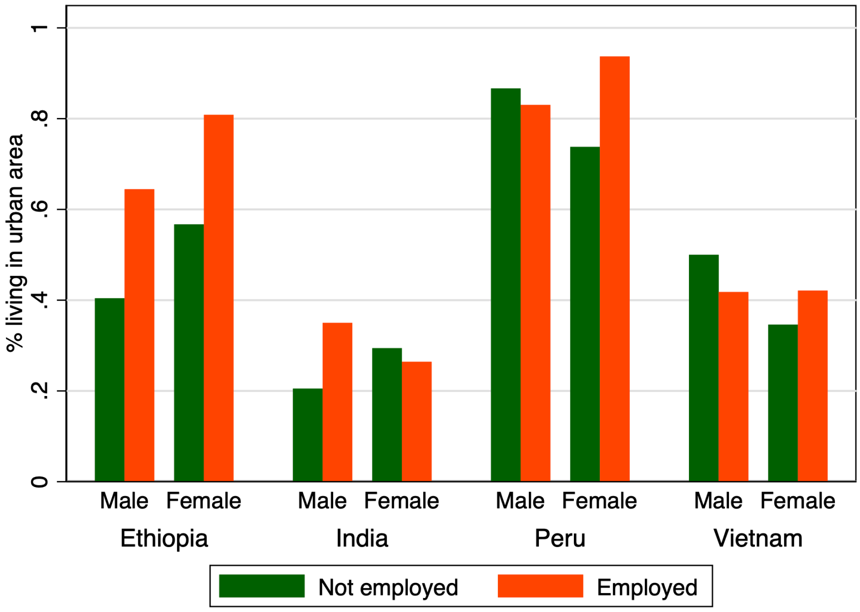


Figure A4: Urban status by gender and employment status



7.3 Robustness checks

Table A17: Two-step Heckman Selection on log earnings

	Ethiopia	India	Peru	Vietnam
2nd Step				
Female	-0.250	-1.122*	-0.212*	-0.165*
	(0.407)	(0.648)	(0.127)	(0.098)
Non-Cognitive Skills	-0.048	-0.085	0.062	0.051
	(0.132)	(0.085)	(0.064)	(0.043)
Female × Non-Cognitive Skills	0.317**	0.185	-0.010	0.016
	(0.140)	(0.145)	(0.090)	(0.052)
Cognitive Skills	0.135	0.278***	0.115*	0.172***
	(0.114)	(0.054)	(0.062)	(0.048)
Female × Cognitive Skills	0.048	0.022	0.043	-0.056
	(0.307)	(0.105)	(0.146)	(0.079)
Selection				
Female	-0.514***	-1.082***	-0.501***	-0.560***
	(0.118)	(0.101)	(0.151)	(0.128)
Non-Cognitive Skills	0.134	-0.135	0.193	0.182
	(0.108)	(0.103)	(0.147)	(0.135)
Female × Non-Cognitive Skills	-0.050	0.186	0.049	-0.186
	(0.130)	(0.133)	(0.196)	(0.171)
Cognitive Skills	-0.081	0.013	-0.219	0.025
	(0.077)	(0.096)	(0.145)	(0.108)
Female × Cognitive Skills	0.320***	-0.030	0.645**	0.229
	(0.116)	(0.119)	(0.263)	(0.143)
Stats				
lambda	-0.141	1.069	0.139	0.070
	(1.452)	(0.962)	(0.459)	(0.482)
Bootstrap N	2,797	2,797	2,797	2,797
Effective N	671	856	452	818

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. Heckman selection. The dependent variable is log unconditional earnings. Bootstrapped standard errors clustered at the child level in parentheses. Includes the following controls: age in months, urban/rural residence, cluster fixed effects and a constant.

Table A18: Effect of gender and skill level on pre-covid earnings for sub-sample of employed: OLS estimates

	Ethiopia	India	Peru	Vietnam
Female	-0.290***	-0.428***	-0.181**	-0.152***
	(0.102)	(0.068)	(0.072)	(0.043)
Cognitive Skills	0.128**	0.266***	0.125***	0.172***
	(0.050)	(0.045)	(0.047)	(0.045)
Female × Cognitive Skills	0.075	0.049	0.005	-0.064
	(0.112)	(0.071)	(0.076)	(0.057)
Bootstrap N	5,265	5,265	5,265	5,265
Effective N	350	430	350	695

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. OLS estimates. The dependent variable is log conditional earning. Bootstrapped standard errors clustered at the child level in parentheses. The model includes the following variables: age in months, urban/rural residence, cluster fixed effects, non-cognitive skills, its interaction with gender and a constant.

Table A19: Controlling for years of education

	Ethiopia	India	Peru	Vietnam
Female	-0.621***	-1.243***	-0.390***	-0.376***
	(0.117)	(0.112)	(0.100)	(0.049)
Non-Cognitive Skills	0.025	-0.048	0.109*	0.010
	(0.076)	(0.068)	(0.057)	(0.034)
Female × Non-Cognitive Skills	0.169	0.214	-0.042	0.043
	(0.118)	(0.147)	(0.107)	(0.054)
Cognitive Skills	-0.054	0.278***	0.032	0.076*
	(0.079)	(0.074)	(0.059)	(0.045)
Female × Cognitive Skills	0.337**	0.014	0.255**	0.026
	(0.137)	(0.123)	(0.107)	(0.058)
Years of education	0.057***	0.003	0.045**	0.036***
	(0.018)	(0.016)	(0.020)	(0.010)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	652	830	440	784

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earnings. Bootstrapped standard errors clustered at the child level in parentheses. Includes the following controls: age in months, urban/rural residence, cluster fixed effects and a constant.

Table A20: Controlling for height-for-age

	Ethiopia	India	Peru	Vietnam
Female	-0.584***	-1.219***	-0.378***	-0.330***
	(0.126)	(0.108)	(0.104)	(0.048)
Non-Cognitive Skills	0.019	-0.046	0.115**	0.022
	(0.079)	(0.067)	(0.058)	(0.035)
Female × Non-Cognitive Skills	0.194	0.209	-0.027	0.023
	(0.122)	(0.143)	(0.102)	(0.056)
Cognitive Skills	0.063	0.267***	0.070	0.135***
	(0.070)	(0.059)	(0.057)	(0.036)
Female × Cognitive Skills	0.380***	0.048	0.283***	0.033
	(0.139)	(0.124)	(0.109)	(0.057)
Height-for-age z-score	-0.002	0.079**	0.086**	0.036
	(0.042)	(0.040)	(0.042)	(0.031)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	650	842	434	780

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earnings. Bootstrapped standard errors clustered at the child level in parentheses. Includes the following controls: age in months, urban/rural residence, cluster fixed effects and a constant.

Table A21: Controlling for work experience

	Ethiopia	India	Peru	Vietnam
Female	-0.596***	-1.238***	-0.391***	-0.341***
	(0.121)	(0.112)	(0.103)	(0.047)
Non-Cognitive Skills	0.020	-0.043	0.104*	0.023
	(0.078)	(0.066)	(0.058)	(0.034)
Female × Non-Cognitive Skills	0.190	0.204	-0.021	0.033
	(0.123)	(0.142)	(0.106)	(0.055)
Cognitive Skills	0.071	0.273***	0.105*	0.134***
	(0.067)	(0.063)	(0.059)	(0.039)
Female × Cognitive Skills	0.368***	0.041	0.262**	0.038
	(0.134)	(0.125)	(0.109)	(0.058)
Work experience in years	-0.012	-0.006	0.014	-0.005
	(0.011)	(0.010)	(0.015)	(0.007)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	655	846	441	793

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earnings. Bootstrapped standard errors clustered at the child level in parentheses. Includes the following controls: age in months, urban/rural residence, cluster fixed effects and a constant.

Table A22: Including the top 1% of earners

	Ethiopia	India	Peru	Vietnam
Female	-0.651***	-0.963***	-0.440***	-0.706***
	(0.119)	(0.157)	(0.104)	(0.218)
Non-Cognitive Skills	-0.108	0.024	0.149**	-0.688
	(0.115)	(0.083)	(0.064)	(0.434)
Female × Non-Cognitive Skills	0.365**	-0.065	-0.065	0.767*
	(0.146)	(0.151)	(0.109)	(0.441)
Cognitive Skills	0.067	0.251***	0.137**	-0.008
	(0.075)	(0.082)	(0.063)	(0.129)
Female × Cognitive Skills	0.425***	0.184	0.220**	0.074
	(0.145)	(0.236)	(0.107)	(0.139)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	662	854	445	801

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earnings. Bootstrapped standard errors clustered at the child level in parentheses. Includes the following controls: age in months, urban/rural residence, cluster fixed effects and a constant.

Table A23: Controlling for marriage status

	Ethiopia	India	Peru	Vietnam
Female	-0.543***	-1.180***	-0.375***	-0.338***
	(0.127)	(0.118)	(0.107)	(0.052)
Non-Cognitive Skills	0.013	-0.044	0.112*	0.024
	(0.079)	(0.067)	(0.059)	(0.038)
Female × Non-Cognitive Skills	0.224*	0.209	-0.019	0.058
	(0.121)	(0.141)	(0.105)	(0.061)
Cognitive Skills	0.068	0.281***	0.075	0.145***
	(0.068)	(0.058)	(0.062)	(0.039)
Female × Cognitive Skills	0.367***	0.040	0.266**	0.021
	(0.138)	(0.122)	(0.116)	(0.063)
Married at age 19	-0.106	-0.063	-0.194	-0.048
	(0.406)	(0.182)	(0.193)	(0.086)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	624	836	426	740

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earnings. Bootstrapped standard errors clustered at the child level in parentheses. Includes the following controls: age in months, urban/rural residence, cluster fixed effects and a constant.

Table A24: Controlling for having a child below 6 years

	Ethiopia	India	Peru	Vietnam
Female	-0.380***	-1.032***	-0.367***	-0.300***
	(0.124)	(0.117)	(0.109)	(0.052)
Non-Cognitive Skills	0.026	-0.039	0.101*	0.026
	(0.082)	(0.067)	(0.058)	(0.033)
Female × Non-Cognitive Skills	0.161	0.167	-0.027	0.033
	(0.115)	(0.142)	(0.104)	(0.054)
Cognitive Skills	0.063	0.254***	0.090	0.125***
	(0.072)	(0.059)	(0.059)	(0.038)
Female × Cognitive Skills	0.298**	0.037	0.259**	0.034
	(0.134)	(0.119)	(0.108)	(0.058)
Has child below 6 yrs	-0.785***	-0.522***	-0.133	-0.127*
	(0.174)	(0.122)	(0.101)	(0.068)
Bootstrap N	8,682	8,682	8,682	8,682
Effective N	655	846	441	793

* $p < 0.1$; ** $p < 0.05$; * $p < 0.01$. PPML estimates. The dependent variable is unconditional earnings. Bootstrapped standard errors clustered at the child level in parentheses. Includes the following controls: age in months, urban/rural residence, cluster fixed effects and a constant.

7.4 Cognitive & Non-Cognitive Measures

Table A25: Summary statistics of Cognitive skill measures (Round 3 & 4)

	Mean	SD	Min	Max
Ethiopia: *N = 733*				
Math Test Score	13.296	6.014	0	27
Language Test Score	14.108	4.608	0	23
PPVT Score	150.754	35.710	33	203
India: *N = 818*				
Math Test Score	14.368	6.997	0	29
Language Test Score	14.699	4.187	2	24
PPVT Score	135.153	37.697	31	199
Peru: *N = 527*				
Math Test Score	17.114	5.508	1	28
Language Test Score	16.009	3.670	3	24
PPVT Score	97.689	16.188	37	125
Vietnam: *N = 767*				
Math Test Score	12.901	5.447	0	26
Language Test Score	14.020	4.682	1	23
PPVT Score	169.541	25.019	67	201

Table A26: Summary statistics of non-cognitive skill measures (Round 5)

	Mean	SD	Min	Max
Ethiopia: *N = 733*				
Leadership Index	-0.001	0.795	-2.84	1.7
Teamwork Index	0.009	0.762	-3.04	1.57
Peer relation Index	0.007	0.618	-2.18	1.83
Agency Index	0.019	0.563	-2.13	1.25
Grit Index	0.015	0.483	-1.25	1.32
Big 5 Index: Neuroticism	0.010	0.518	-2.42	1.61
Big 5 Index: Consientiousness	0.012	0.496	-1.59	1.45
Self-Efficacy Index	0.014	0.542	-2.24	1.82
Self-Esteem Index	0.002	0.552	-2.29	1.71
India: *N = 818*				
Leadership Index	0.022	0.863	-2.7	1.68
Teamwork Index	0.013	0.770	-4.03	1.62
Peer relation Index	0.011	0.621	-2.37	1.6
Agency Index	0.029	0.529	-2.27	1.63
Grit Index	0.004	0.456	-1.4	1.39
Big 5 Index: Neuroticism	0.014	0.566	-1.78	1.64
Big 5 Index: Consientiousness	0.009	0.524	-2.28	1.41
Self-Efficacy Index	0.021	0.545	-2.11	1.67
Self-Esteem Index	0.005	0.537	-1.87	1.67
Peru: *N = 527*				
Leadership Index	-0.009	0.795	-2.68	1.77
Teamwork Index	0.023	0.786	-2.48	1.64
Peer relation Index	-0.011	0.667	-2.23	1.98
Agency Index	-0.004	0.561	-2.4	1.65
Grit Index	-0.008	0.451	-1.56	1.51
Big 5 Index: Neuroticism	-0.004	0.580	-2.61	1.57
Big 5 Index: Consientiousness	0.001	0.516	-2.06	1.66
Self-Efficacy Index	0.018	0.613	-2.09	1.78
Self-Esteem Index	0.014	0.592	-2.04	1.81
Vietnam: *N = 767*				
Leadership Index	0.054	0.843	-2.58	2.46
Teamwork Index	0.031	0.799	-3.25	2.3
Peer relation Index	0.026	0.535	-2.67	2.16
Agency Index	0.017	0.554	-2.41	1.37
Grit Index	0.007	0.492	-1.95	1.29
Big 5 Index: Neuroticism	-0.003	0.511	-1.62	1.48
Big 5 Index: Consientiousness	0.004	0.531	-1.85	1.79
Self-Efficacy Index	0.007	0.501	-2.02	1.87
Self-Esteem Index	0.014	0.527	-1.85	2.4

YL Math Test

The math test was administered at age 19 and altered to account for differences in competencies across countries. Questions were grouped into three booklets of increasing difficulty and children started on the second, intermediate booklet. If they performed well on intermediate skills, they then answered questions on advanced skills. But if they performed poorly they moved on to questions on basic skills. Revollo (2018) describes these tests and their internal and external validity.

YL Language Test

At age 19, children's reading comprehension was tested in a similar manner to their mathematical achievement. Comprehension questions were grouped into three booklets – basic, intermediate and advanced comprehension. Children started with questions in booklet 2 and progressed to booklet 1 or 3 depending on their performance. The items administered were country specific. Revollo (2018) describes the design of the reading comprehension test in detail.

Peabody Picture Vocabulary Test (PPVT)

The PPVT was administered to children at age 15 (Round 3) and was designed to measure receptive vocabulary. The children were presented with cards depicting four different scenarios and asked which picture best shows a sentence or word read aloud by the examiner. The questions become increasingly difficult, with the starting point determined by the child's age.

Review of Personal Effectiveness with Locus of Control (ROPELOC)

At age 22 we also make use of two, three-question sub-scales from the ROPELOC measuring their leadership and cooperative teamwork abilities (Richards et al., 2002). The two scales contain questions statements such as I am seen as a capable leader and I am good at cooperating with team members respectively. Children are asked to what extent they agree these statements describe themselves, with possible responses being on a 4-point scale from strongly agree to strongly disagree. After being assigned numeric values, we sum the responses within each sub-scale and calculate the z-score.

Marsh Self-Description

At age 22, we also use two sub-scales of the Marsh Self-description Questionnaires measuring peer relations and general self-esteem. Each sub-scale is comprised of eight statements about self-concept in the respective domain. These statements are presented to children, who are then asked to what extent they agree or disagree with them, such as I get along with other kids easily or a lot of things about me are good. Once again, the possible responses to these statements range from strongly agree to strongly disagree, which we assign numeric values, sum them and calculate the z-score. Yorke & Ogando (2018) provides more detailed information on theoretical concepts underpinning the Marsh Self-description questionnaires and the validity of their structure.

Young Lives Psychosocial Scales

We use a scale measuring agency at age 22 from the Young Lives survey, based on Rotter (1966) and Bandura (1993). The scale poses a number of statements about the degree of control the child has on their own life, such as If I try hard I can improve my situation in my life and I like to make plans for my future studies and work. The responses are assigned a numeric value and summed to calculate the z-score. More detailed information on the construction and validity of this measure is described in Yorke & Ogando (2018).

Duckworth and Quinn Grit Scale

At age 22, we use measures of two aspects of grit as designed by Duckworth and Quinn (2009). These sub-scales are shortened versions of those first proposed in Duckworth et al. (2007), measuring 'consistency of interest' and 'perseverance of effort'. These assessments involve presenting children with several statements about the relevant aspect of grit, such as I often set a goal but choose to pursue a different one and I finish whatever I begin. The child is asked to what extent they agree the statements describe themselves on a 5-point scale, from not like me at all to very much like me. We sum these responses and calculate the z-score.

Big Five Inventory

Also at age 22, we use two components of the Big Five Inventory - conscientiousness and neuroticism. They contain eight and nine statements respectively and respondents are asked the extent to which they agree that these statements describe them, such as I am someone who does a thorough job or I am someone who is relaxed and handles stress well. Responses are on a 5-point scale from strongly agree to strongly disagree and are assigned a numerical value. The responses summed within each of the two components and the z-score is calculated.

General Self-Efficacy

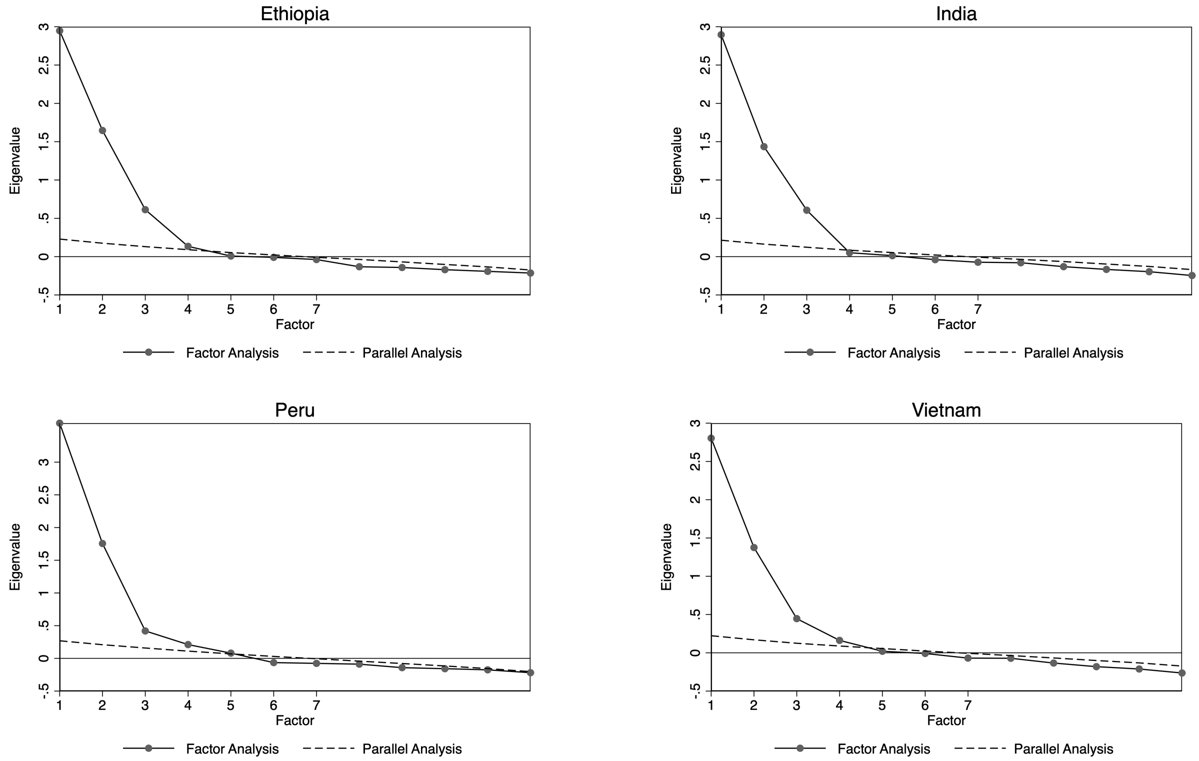
At age 22, we use a general self-efficacy scale adapted from Jerusalem & Schwarzer (1979). This scale measures an individuals' self-determination and ability to cope with adversity. These assessments involve presenting children with several statements such as I can always manage to solve difficult problems if I try hard enough, and then asking them to what extent they agree/disagree with the statements on a 4-point scale. The responses are assigned a numeric value and summed to calculate the z-score.

7.5 Initial Exploratory Factor Analysis

In our initial exploratory factor analysis, we examine whether our observable measures sufficiently capture the variation in the latent variables. We first analyze the extent of the shared variation in the observable measures and retain the underlying factors based on the eigenvalues and a parallel analysis, as proposed by Horn (1965).

We use both the cognitive and non-cognitive skill measures described in Appendix D in our EFA. Figure E1 shows a scree plot with the eigenvalues of factors in order of magnitude. Using Horn (1965)'s rule-of-thumb, the figure would suggest that these measures have enough variation to retain between 3 and 4 factors in the four countries. However, Cattell (1966) suggests retaining only the factors whose eigenvalues are larger than that of the factor at which the first large drop in eigenvalue occurs. In Figure E1, such a drop occurs at factor 3. Moreover, Kaiser (1960) suggests keeping only factors with eigenvalue greater than or equal to 1. Together, these criteria suggest that these measures are rich enough to capture at least the two underlying factors we ex-ante believe to be underlying these measures.

Figure A5: Eigenvalues from EFA and parallel analysis of socio-emotional and cognitive skills



Having verified that the measures share meaningful variation with which to capture their underlying factor, we then establish the relationship between each measure and the retained factor by estimating their factor loadings. Table E1 shows the rotated factor loadings and unique variance associated with each measure of human capital in each country. We rotate the factor loadings using the oblique quartimin rotation, which allows the underlying factors to be correlated. We can see a clear divide between those measures that we ex-ante believe measure cognitive skills and non-cognitive skills. For example, in Ethiopia, the non-cognitive skills load heavily on Factor 1 and the cognitive skills load heavily on Factor 2.

Table A27: EFA of socio-emotional and cognitive skills, extracting 2 factors

	Factor 1	Factor 2	Uniqueness
Ethiopia			
Leadership Index	0.501	0.088	0.737
Teamwork Index	0.556	0.037	0.687
Peer relation Index	0.661	-0.151	0.550
Agency Index	0.451	0.172	0.759
Grit Index	0.270	0.149	0.901
Big 5 Index: Neuroticism	0.365	0.131	0.845
Big 5 Index: Consientiousness	0.551	0.137	0.670
Self-Efficacy Index	0.736	0.003	0.458
Self-Esteem Index	0.785	-0.044	0.385
Math Test Score	0.026	0.812	0.338
Language Test Score	-0.041	0.799	0.362
PPVT Score	0.036	0.535	0.711
N	733		
India			
Leadership Index	0.390	0.040	0.839
Teamwork Index	0.535	0.123	0.669
Peer relation Index	0.630	-0.144	0.623
Agency Index	0.235	0.335	0.796
Grit Index	0.428	0.096	0.789
Big 5 Index: Neuroticism	0.427	0.197	0.741
Big 5 Index: Consientiousness	0.562	0.115	0.642
Self-Efficacy Index	0.595	0.069	0.622
Self-Esteem Index	0.653	-0.135	0.595
Math Test Score	0.028	0.776	0.387
Language Test Score	-0.032	0.781	0.401
PPVT Score	0.002	0.659	0.565
N	818		
Peru			
Leadership Index	0.655	-0.054	0.582
Teamwork Index	0.603	0.083	0.611
Peer relation Index	0.594	-0.152	0.658
Agency Index	0.432	0.346	0.638
Grit Index	0.441	0.189	0.738
Big 5 Index: Neuroticism	0.271	0.168	0.882
Big 5 Index: Consientiousness	0.634	0.058	0.581
Self-Efficacy Index	0.779	-0.008	0.395
Self-Esteem Index	0.816	-0.039	0.345
Math Test Score	-0.022	0.794	0.376
Language Test Score	0.002	0.786	0.382
PPVT Score	-0.004	0.735	0.461
N	527		
Vietnam			
Leadership Index	0.508	0.165	0.687
Teamwork Index	0.390	0.155	0.805
Peer relation Index	0.573	-0.141	0.678
Agency Index	0.358	0.258	0.776
Grit Index	0.528	-0.009	0.722
Big 5 Index: Neuroticism	0.434	0.041	0.804
Big 5 Index: Consientiousness	0.588	-0.005	0.655
Self-Efficacy Index	0.649	0.057	0.564
Self-Esteem Index	0.714	-0.076	0.502
Math Test Score	0.028	0.755	0.422
Language Test Score	-0.036	0.731	0.473
PPVT Score	-0.008	0.519	0.732
N	767		

7.6 Measurement System

In the previous section, we established that the observed measures have sufficient variation to capture two latent variables – cognitive and non-cognitive skills. We assume these skills can be proxied with error by existing observable measures, and specify a linear relationship between these measures and the latent skills.

Hence, for individual i and skill j:

$$Z_{imj} = \mu_{mj} + \lambda_{imj}\theta_j + \epsilon_{imj} \qquad \text{for} \quad j \in \{c, s\}$$

where θ_j represents the latent skill, Z_{mcj} is the mth observable measure of skill j, μ_{mcj} is the mean of the measurement and ϵ_{mcj} is the measurement error. The factor loading λ_{mcj} indicates the extent to which the measured item is related to the latent variable.

Stacking these equations across measures and skills:

$$\boldsymbol{Z} = \boldsymbol{\mu} + \boldsymbol{\lambda}\boldsymbol{\theta} + \boldsymbol{\epsilon}$$

where

$$\begin{aligned}
\boldsymbol{\mu} &= (\mu_{mc}, \mu_{ms})^T \\
\boldsymbol{\theta} &= (\theta_{mc}, \theta_{ms})^T \\
\boldsymbol{\epsilon} &= (\epsilon_{mc}, \epsilon_{ms})^T
\end{aligned}$$

and

$$\boldsymbol{\lambda}_c = \begin{bmatrix} \lambda_{mc} & 0 \\ 0 & \lambda_{ms} \end{bmatrix} \tag{4}$$

Assuming the measurement errors are independent of the latent variables, the variance of the observable measures can be expressed as a function of variation in the latent variables and the measurement error:

$$\begin{aligned}
Var(\boldsymbol{Z}) &= \boldsymbol{\lambda} Var(\boldsymbol{\theta})\boldsymbol{\lambda}^T + Var(\boldsymbol{\epsilon}) \\
\boldsymbol{\Sigma} &= \boldsymbol{\lambda}\boldsymbol{\Theta}\boldsymbol{\lambda}^T + \boldsymbol{\Psi}
\end{aligned}$$

where $\boldsymbol{\Sigma}$, $\boldsymbol{\Theta}$, $\boldsymbol{\Psi}$ are the respective covariance matrices of the observed data, latent skills and measurement errors respectively. As is standard in the factor analysis literature, we assume that

$$\boldsymbol{\theta} \sim N(\boldsymbol{\kappa}, \boldsymbol{\Theta})$$
$$\boldsymbol{\epsilon} \sim N(0, \boldsymbol{\Psi})$$

We impose a minimum set of restriction on the structure of the measurement model, so that the parameters are identifiable.

1. $\boldsymbol{\kappa} = \mathrm{E}[\boldsymbol{\theta}] = \mathbf{0}$
2. $\mathrm{diag}(\boldsymbol{\Psi}) = I$
3. $\mathrm{diag}(\boldsymbol{\Theta}) = I$
4. $\lambda_{ij} = 1$ for all j, where $m = 1$ is arbitrarily chosen

We estimate the system by maximum likely to back out estimates of the latent skills. Because these estimates are random variables – being a function of data and an estimator – when we can include them in our regressions. However, the standard OLS assumption that the regressors are fixed is violated in this case, and so we use bootstrapped standard errors.