

DISCUSSION PAPER SERIES

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to Higher Education in a Developing
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ABSTRACT

What Stops Poor Girls from Going to College? Skill Development and Access to Higher Education in a Developing Country

Although recent evidence suggests that the aggregate gender gap in access to Higher Education in Peru has been closed, differences in enrollment between the poor and the rich are still notably larger among girls. This paper explores the factors behind these gender differences in access to Higher Education. Specifically, we assess whether larger socioeconomic disparities among females can be explained by long-run factors crystallized in Higher Education preparedness (i.e., cognitive and non-cognitive skills), rather than by short-term economic constraints. We employ a rich longitudinal data set that allows for the estimation of a structural model of skill formation from early childhood. Our results show that cognitive abilities are strong predictors of enrollment for both genders, whereas non-cognitive skills are only determinant among boys. We also provide strong evidence of gender-specific short-term barriers in access to post-secondary schooling: while differences in skills are the major determinants of the wealth gradient for males, the female gap remains large even after accounting for these factors. Further analysis reveals that access to Higher Education among girls is overly sensitive to marginal costs of enrollment, suggesting that at least part of this gradient might be explained by lower expected returns rather than credit constraints. Overall, these findings illustrate the importance of early human capital investments on educational attainment, but also point to the prevalence of short-term restrictions that disproportionately affect females in disadvantaged households.

JEL Classification: I23, J16, J24

Keywords: higher education, gender, skills

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1. Introduction

During the last decades, access to Higher Education has increased steadily in Peru, and recent evidence suggests that the gender gap in enrollment has virtually closed¹. However, socioeconomic disparities in enrollment are still notably larger among females, with girls in poor households presenting much lower enrollment rates than their male counterparts. This paper explores the factors behind these gender differences in access to Higher Education. Specifically, we assess whether the larger wealth gradient among females can be explained by long-run factors crystalized in Higher Education preparedness (i.e., cognitive and non-cognitive skills), rather than by short-term economic constraints.

While the determinants of access to Higher Education have been studied extensively in developed countries, data limitations have made it difficult to address the role of human capital endowments in the transition to post-secondary schooling in developing countries. We fill this gap by taking advantage of the Young Lives dataset, a longitudinal study that tracks a cohort of Peruvian children from early childhood until after most of them have made the transition to work or post-secondary education. The availability of detailed measures on cognitive and non-cognitive skills throughout the different stages of childhood, as well as a rich set of indicators of family environment and parental investments in education, allow us to estimate a structural model of skill formation that addresses the endogeneity concerns typically encountered in the literature. Therefore, our key contribution is to reliably identify the causal effect of skill endowments during adolescence on enrollment in Higher Education, which in turn lets us explore the factors that explain the remaining socioeconomic disparities among boys and girls.

Our results show that although both cognitive and non-cognitive skills during adolescence are similarly distributed across genders, their effect on access to Higher Education differs. Cognitive skills substantially increase the probability of enrolling in Higher Education for both genders, but non-cognitive skills seem to matter only for boys. Moreover, we document the prevalence of gender-specific socioeconomic barriers in access to Higher Education. While accounting for human capital endowments explains almost the totality of the wealth gradient among boys, a substantial fraction of the female gap in enrollment remains unexplained. We provide suggestive evidence that higher sensibility to the costs of attending Higher Education might be a potential explanation for these differences.

¹ According to the country's household surveys, approximately 50% of both boys and girls now attend some form of post-secondary schooling.

The remaining of this paper is organized as follows. In Section 2, we provide a brief review of the literature on human capital and access to Higher Education, with a focus in developing countries. In Section 3, we describe our empirical strategy and the main characteristics of our dataset and study sample. In Section 4, we present and discuss our results. Section 5 concludes.

2. Background

The literature in developed countries argues that the socioeconomic disparities in access to Higher Education are mostly explained by long-term consequences of low income, such as lower human capital endowments that result from a poor environment during childhood². In Peru, Castro et al. (2016) document that the strong correlation between socioeconomic status and educational attainment among urban workers might be partly explained by skills and other background factors. However, recent studies in developing countries suggest that short-term economic factors may also play an important role in determining Higher Education enrollment in such settings (Li, 2007; Melguizo et al., 2016; Solís, 2017). For instance, Kaufmann (2014) finds in Mexico that the poor require higher perceived returns to Higher Education in order to enroll, which the author interprets as a sign of credit constraints.

Despite this growing body of evidence, studies that explore the relationship between human capital endowments and the wealth gradient in access to Higher Education in developing countries remain scarce. A notable exception is a paper by Sánchez & Singh (2016), which uses data from four developing countries including Peru to show that only a small fraction of socioeconomic differences in educational attainment is explained by parental and child aspirations. Nevertheless, most existing studies on this issue still rely on cross-sectional surveys with poor measures of skills and subject to concerns about reverse causality. Moreover, very little is known about the potential gender heterogeneity in relationship between skill development and access to Higher Education.

3. Methods

3.1. Empirical strategy

To address our research questions, we take advantage of the longitudinal nature of the Young Lives study to estimate a structural model of skill formation as proposed by Cunha & Heckman (2007, 2008). This methodology treats cognitive and non-cognitive skills as complementary latent factors that are shaped by an individual's innate traits, previous skill endowments, and the external inputs received during the different stages of child development.

² See, for example, Keane & Wolpin (2001), Carneiro & Heckman (2002) and Cameron & Taber (2004).

Specifically, we employ a full information maximum likelihood method to estimate the following model:

$$\theta_{i,t}^C = \beta_{t,0}^C + \beta_{t,1}^C \theta_{i,t-1}^C + \beta_{t,2}^C \theta_{i,t-1}^N + \beta_{t,3}^C I_{i,t-1} + \beta_{t,4}^C X_{i,t} + \beta_{t,5}^C X_{i,0} + \epsilon_{i,t}^C$$

$$\theta_{i,t}^N = \beta_{t,0}^N + \beta_{t,1}^N \theta_{i,t-1}^C + \beta_{t,2}^N \theta_{i,t-1}^N + \beta_{t,3}^N I_{i,t-1} + \beta_{t,4}^N X_{i,t} + \beta_{t,5}^N X_{i,0} + \epsilon_{i,t}^N$$

Where θ_t^C and θ_t^N denote a child's cognitive and non-cognitive skills in survey round, X_t and X_0 are sets of contemporary and initial child characteristics, and I_t represents parental investments in skill development. We allow the error terms ϵ_t^C and ϵ_t^N to be correlated in a given round. Both types of skills, as well as our measure of parental investments, are estimated using exploratory factor analysis. Appendix Table 1 describes the variables we used to estimate these latent factors.

Our model assumptions and variable selection follow Helmers & Patnam (2011) and Sánchez (2017), who also study skill development using the Young Lives dataset³. However, we extend their analysis by allowing all coefficients to differ between boys and girls. This way, the model captures the variation in the determinants of skills development across the different stages of child development, as well as the gender differences in this process.

To analyze the relationship between skill endowments and enrollment in Higher Education, we add the following equation to the model:

$$S_{t=4} = \beta_{S,0} + \beta_{S,1} \theta_{t=3}^C + \beta_{S,2} \theta_{t=3}^N + \beta_{S,4} X_{t=3} + \beta_{S,5} X_0 + \epsilon_{t=4}^S$$

$S_{t=4}$ is a binary variable indicating whether the individual is enrolled in any kind of Higher Education (i.e., technical or university studies) in the last available round of the study ($t = 4$). By addressing the concerns that typically arise from measurement errors and other confounding factors, we are to reliably identify the causal effect of both types of skills on access to Higher Education.

3.2. Data and descriptive statistics

The Young Lives dataset tracks a cohort of 714 Peruvian children over four survey rounds from early childhood until they are around 19 years old – a time when most of them have either enrolled in Higher Education or finished their studies. The sample of households included in the study covers the full diversity of children in Peru (Escobal & Flores, 2008). In each survey round, a rich set of background variables about each child is collected. In particular, we exploit the

³ However, their studies only focused on the development of skills through childhood, rather than their effect on adult outcomes.

availability of multiple measures of cognitive and non-cognitive skills, as well as many indicators of parental investment in their education development, to construct the variables used in our analysis.

In Table 1, we provide summary statistics by gender and for the whole sample. For the variables that vary over time, we use the measures from Round 3 of the Young Lives study, when children are approximately 15 years old and have yet to finish secondary school. Boys and girls are well-balanced across most variables employed in our analysis, with the exception of the percentage of caregivers with secondary education and the height-for-age z-score – a proxy of nutritional status. Interestingly, no significant differences are found in our indexes of cognitive and non-cognitive skills. We analyze this result further in section 4.1. We restrict our analysis to subjects that are present in all survey rounds, which leaves us with a final sample of 635 children. This accounts for 88.9% of the initial sample. In the last row of Table 1, we show that attrition rates are not statistically different between boys and girls, and are thus unlikely to bias our results.

Table 2 shows that the relationship between wealth during adolescence and educational attainment in our sample is very similar to what is observed in the country's household surveys. Panel A shows that completion of secondary school is correlated with wealth, but this relationship is similar across genders. If anything, the share of girls that have finished secondary school by the last Round of the study is slightly higher in all wealth terciles. In contrast, section B of Table 2 shows that the wealth gradient in access to Higher Education is more pronounced, specially so among girls. In fact, female children in the bottom tercile of wealth are 15 percentage points less likely to enroll in Higher Education than their male counterparts. The goal of this study is to explore the factors behind the surge of this gender gap in the transition from secondary to Higher Education.

4. Results

4.1. Skills as determinants of access to Higher Education

In Section 2, we discussed the possibility that Higher Education preparedness (i.e., human capital endowments) is behind the wealth gradient in enrollment to post-secondary schooling. However, in Section 3.2 we noted that there is no statistical difference between boys and girls in terms of their mean endowments of cognitive and non-cognitive skills right before they complete secondary schooling. In Figures 1 and 2, we provide evidence that the relationship between wealth during adolescence and skill endowments is also similar across genders, for all levels of the wealth distribution. Although lower levels of household wealth are associated with both lower cognitive and non-cognitive skills, this relationship is not more pronounced among

girls. This implies that the large gap in access to Higher Education faced by poor women cannot be explained by lower levels of human capital.

Nevertheless, it is possible that boys and girls face different returns to their endowments of human capital in terms of the probability of enrolling in Higher Education. We present our estimates of a standard model of access to Higher Education in columns (1) and (2) of Table 3. In line with the preliminary discussion, household wealth during adolescence is found to be more than twice as important for girls than for boys in determining enrollment. While boys in the top tercile of the distribution are approximately 17 percentage points more likely to attend Higher Education than male children in the bottom tercile, the corresponding figure for females is as high as 37 percentage points. Contrary to what is typically found in the literature, we find that this relationship is not driven by the education level of the child's caregiver. Moreover, we extend our model to account for multiple measures of family disadvantage throughout the early stages of childhood development in columns (3) and (4), but find no evidence that the wealth gap in educational attainment is driven by these factors.

Our main results are presented in columns (5) and (6) of Table 3. Following the framework developed in Section 3.1, we estimate the enrollment decision jointly with the structural model of skill formation, and include predicted cognitive and non-cognitive skills during adolescence as determinants of access to Higher Education. The results provide compelling evidence that human capital endowments are important determinants of enrollment in post-secondary schooling, but also show that this relationship differs according to the gender of the child. Specifically, a one standard deviation increase in our latent measure of cognitive skills increases the probability of attending some form of post-secondary schooling in 11.8 and 17 percentage points among boys and girls, respectively (significant at the 1% level). In contrast, non-cognitive skills are only found to be significant for boys, with a corresponding effect of 5.9 percentage points on the outcome variable. Among girls, non-cognitive skills do not seem to affect the probability of enrolling in Higher Education.

In line with the literature, socioeconomic status turns out to be highly correlated with college preparedness (which in turn depends on long-term income and other related factors) in our setting. After accounting for cognitive and non-cognitive skills, the coefficients of short-term wealth decrease substantially and in similar magnitude for both genders. Nevertheless, the findings in columns (5) and (6) provide strong evidence of gender-specific short-term barriers in access to post-secondary schooling: while skills account for almost the entire wealth gradient among males, the female gap remains large even after controlling for human capital

endowments. Specifically, girls in the middle and top terciles of the wealth distribution are 18.6 and 28 percentage points more likely to enroll in Higher Education, conditional on their cognitive and non-cognitive skills and a rich set of household and family background variables.

4.2. Exploring the gender-specific wealth gap

Interpreting gender-specific socioeconomic disparities in light of the mainstream literature is not straightforward. According to a standard model of investment in human capital, a significant coefficient on short-term wealth implies the existence of binding credit constraints⁴. However, provided that child gender is random, credit-constraints should not affect girls differently. Moreover, Table 1 shows that the probability that a girl enrolls in Higher Education is not affected by the number or gender of her siblings. Nevertheless, we provide a direct test of credit constraints in columns (1) and (2) of Table 4. We address these questions through the inclusion of a binary indicator for whether the child's caregiver reported having access to credit in Round 3 of the Young Lives study. Interestingly, the effect of this variable on enrollment is zero for both boys and girls, and the wealth coefficients do not change after its inclusion. Despite the limitations of the employed indicator, these results are indicative that other mechanisms aside from credit constraints could be in play.

Another possibility is that larger socioeconomic disparities between girls could be driven by lower perceived marginal returns to education. In this case, human capital investments among females would be more sensitive to changes in the marginal costs and benefits of attending post-secondary schooling. Although it is impossible to account for all such factors, we include an additional variable in the model that indicates whether an individual lives more than one hour away from the nearest Higher Education institution in Round 3 of the Young Lives study. Following Kaufmann (2014), we assume that a larger distance substantially increases the direct cost of studying, particularly when daily commute is no longer possible. Moreover, the wealth index during adolescence and our indicator for the distance to the nearest Higher Education institution exhibit a correlation of -0.45, indicating that children in the lowest percentiles of the wealth distribution face higher transportation costs.

The results of this exercise are striking (see columns (3) and (4) of Table 2). While the distance dummy has no effect among boys, it significantly decreases the probability of enrolling by 18.6 percentage points among girls (even when controlling for rural location of the household). This variable alone accounts for 25% of the gap between girls in the bottom and top terciles of the

⁴ See Lochner & Monge-Naranjo (2011, 2012).

wealth distribution. Although we have no way of assuring that the distance to the nearest Higher Education institution is exogenous to all other child and household characteristics, note that these results are conditional on our indicator for whether the household is located in a rural area. Overall, we conclude that these findings provide suggestive evidence that girls face lower perceived returns to Higher Education, and are therefore more sensitive to increases in the costs of enrolling.

Conclusion

In this paper, we have taken advantage of the unique nature of the Young Lives study to identify the importance of early human capital investments on educational attainment in the context of a developing country. By modeling skill formation as a dynamic process that depends on environmental factors and external inputs throughout a child's development, we are able to show that lower socioeconomic status has important long-term consequences on Higher Education preparedness (i.e., cognitive and non-cognitive skills), which in turn explains a large portion of the wealth gradient in enrollment. To the best of our knowledge, this is the first study to causally estimate the effect of human capital endowments on the probability of enrolling in Higher Education in a developing country.

Moreover, contribute to the literature by focusing on the gender differences in the relationship between skills and access to Higher Education. Our results confirm that while the distribution of skills during adolescence is similar across genders, their returns in term of the probability of enrolling in post-secondary education differ. Both males and females benefit from higher cognitive skills, but non-cognitive skills only have a significant effect among males. We also document the prevalence of short-term economic restrictions that disproportionately affect females in disadvantaged households. Although the literature typically interprets this as evidence of credit constraints, we provide suggestive evidence that these differences might be driven, at least partly, by lower marginal expected returns to investment in human capital among girls. However, more research is needed to completely understand how gender and wealth interact in the transition to Higher Education.

References

- Almlund, M., Duckworth, A., Heckman, J., & Kautz, T. (2011). Personality Psychology and Economics. En E. Hanushek, S. Machin, & L. Woessman, *Handbook of the Economics of Education* (Vol. 4, págs. 1-181). Amsterdam: Elsevier.
- Cameron, S., & Taber, C. (2004). Estimation of Educational Borrowing Constraints using Returns to Schooling. *Journal of Political Economy*, 112(1), 132-182.
- Carneiro, P., & Heckman, J. J. (2002). The Evidence on Credit Constraints in Post-Secondary Schooling. *Economic Journal*, 112(482), 705-734.
- Castro, J. F., Yamada, G., & Arias, O. (2016). Higher education decisions in Peru: on the role of financial constraints, skills, and family background. *Higher Education*, 72, 457-486.
- Cunha, F., & Heckman, J. J. (2007). The Technology of Skill Formation. *American Economic Review*, 97(2), 31-47.
- Cunha, F., & Heckman, J. J. (2008). Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation. *Journal of Human Resources*, 43(4), 738-782.
- Heckman, J. J., Stixrud, J., & Urzua, S. (2006). The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior. *Journal of Labor Economics*, 24(3), 411-482.
- Helmets, C., & Patnam, M. (2011). The formation and evolution of childhood skill acquisition: Evidence from India. *Journal of Development Economics*, 95, 252-266.
- Kaufmann, K. M. (2014). Understanding the income gradient in college attendance in Mexico: the role of heterogeneity in expected returns. *Quantitative Economics*, 5, 583-630.
- Keane, M. P., & Wolpin, K. I. (2001). The Effect of Parental Transfers and Borrowing Constraints on Educational Attainment. *International Economic Review*, 42(4), 1051-1103.
- Li, W. (2007). Family background, financial constraints and higher education attendance in China. *Economics of Education Review*, 26(6), 724-734.
- Lindqvist, E., & Vestman, R. (2011). The Labor Market Returns to Cognitive and Noncognitive Ability: Evidence from the Swedish Enlistment. *American Economic Journal: Applied Economics*, 3, 101-128.
- Lochner, L. J., & Monge-Naranjo, A. (2011). The Nature of Credit Constraints and Human Capital. *American Economic Review*, 101(6), 2487-2529.
- Lochner, L. J., & Monge-Naranjo, A. (2012). Credit Constraints in Education. *Annual Review of Economics*, 4, 225-256.
- Melguizo, T., Sánchez, F., & Velasco, T. (2016). Credit for Low-Income Students and Access to and Academic Performance in Higher Education in Colombia: A Regression Discontinuity Approach. *World Development*, 80(C), 61-77.
- Sánchez, A. (2017). The structural relationship between early nutrition, cognitive skills and non-cognitive skills in four developing countries. *Economics & Human Biology*, 27, 33-54.

Sánchez, A., & Singh, A. (2016). *Accessing Higher Education in Developing Countries: Panel Data Analysis from India, Peru, and Vietnam*. Young Lives Working Paper, 150.

Table 1: Descriptive statistics by gender during adolescence

	Whole Sample (1)	Male (2)	Female (3)	p-value (M = F) (4)
<i>Skill endowments (15 years old)</i>				
- Cognitive skills (standardized index)	0.000 (0.129)	0.01 (0.139)	-0.012 (0.138)	0.830
- Non-cognitive skills (standardized index)	0.000 (0.057)	-0.039 (0.067)	0.044 (0.085)	0.422
<i>Wealth Index (15 years old)</i>				
- Bottom wealth tercile (%)	0.318 (0.070)	0.293 (0.069)	0.348 (0.076)	0.145
- Middle wealth tercile (%)	0.322 (0.033)	0.345 (0.039)	0.296 (0.033)	0.130
- Top wealth tercile (%)	0.305 (0.054)	0.295 (0.052)	0.317 (0.060)	0.383
<i>Caregiver's education (highest completed level in Round 1 of the study)</i>				
- Primary education or less (%)	0.675 (0.045)	0.656 (0.046)	0.698 (0.048)	0.129
- Secondary Education (%)	0.244 (0.034)	0.266 (0.036)	0.218 (0.035)	0.067
- Higher Education (%)	0.081 (0.017)	0.078 (0.017)	0.084 (0.019)	0.617
<i>Rural household (15 years old)</i>				
	0.233 (0.070)	0.221 (0.069)	0.247 (0.074)	0.403
<i>Height-for-age z-score (15 years old)</i>				
	-1.476 (0.082)	-1.374 (0.106)	-1.591 (0.066)	0.012
<i>Family structure (15 years old)</i>				
- Child has an older sibling	0.693 (0.025)	0.699 (0.029)	0.686 (0.029)	0.669
- Number of brothers	1.045 (0.051)	1.084 (0.061)	1.000 (0.052)	0.114
- Number of sisters	0.867 (0.043)	0.887 (0.052)	0.844 (0.052)	0.470
<i>Family disadvantage</i>				
- Migrated before 8 years old	0.315 (0.053)	0.311 (0.058)	0.320 (0.059)	0.846
- Indigenous background	0.321 (0.078)	0.335 (0.083)	0.305 (0.076)	0.370
- One parent absent (8 years old)	0.238 (0.021)	0.231 (0.026)	0.247 (0.025)	0.598
- Born to a teenage mother	0.178 (0.017)	0.161 (0.025)	0.198 (0.022)	0.266
- Caregiver's partner gets drunk at least once a week (8 years old)	0.555 (0.031)	0.549 (0.042)	0.562 (0.032)	0.770
Initial sample size	714	386	328	-
Present in all survey rounds (%)	0.889	0.883	0.896	0.668

Table 2: Secondary school completion and enrollment in Higher Education, by gender and household wealth during adolescence

	Male (1)	Female (2)	Whole sample (3)
<i>Panel A. Completion of secondary school</i>			
Bottom wealth tercile	57.28%	61.17%	59.22%
Middle wealth tercile	67.19%	70.79%	68.66%
Top wealth tercile	82.86%	90.00%	86.34%
Total	69.05%	73.97%	71.34%
<i>Panel B. Enrollment in Higher Education</i>			
Bottom wealth tercile	39.33%	24.44%	31.84%
Middle wealth tercile	44.44%	52.44%	47.74%
Top wealth tercile	70.10%	71.43%	70.77%
Total	51.16%	50.00%	50.61%
Observations	341	294	635

Table 3: Structural model of enrollment in Higher Education – main results

	A		B		C	
	Male (1)	Female (2)	Male (3)	Female (4)	Male (5)	Female (6)
<i>Wealth index (15 years old)</i>						
- Middle tercile	-0.020 (0.067)	0.237** (0.111)	-0.016 (0.066)	0.241** (0.110)	-0.106 (0.069)	0.186* (0.104)
- Top tercile	0.172** (0.071)	0.368*** (0.105)	0.165** (0.065)	0.365*** (0.110)	0.068 (0.065)	0.280** (0.116)
<i>Caregiver's education</i>						
- Secondary School	-0.011 (0.086)	0.061 (0.106)	0.002 (0.087)	0.094 (0.100)	-0.036 (0.082)	0.038 (0.092)
- Higher Education	0.192* (0.115)	0.146 (0.090)	0.184 (0.118)	0.141 (0.086)	0.122 (0.111)	0.057 (0.080)
<i>Rural household (15 years old)</i>						
	0.024 (0.061)	0.013 (0.102)	0.004 (0.061)	-0.006 (0.104)	0.016 (0.067)	0.080 (0.099)
<i>Height-for-age z-score (15 years old)</i>						
	0.085*** (0.021)	0.088** (0.038)	0.085*** (0.020)	0.075** (0.039)	0.069*** (0.019)	0.036 (0.036)
<i>Family structure (15 years old)</i>						
- Child has an older sibling	-0.140*** (0.049)	-0.001 (0.076)	-0.144** (0.058)	0.047 (0.066)	-0.132** (0.057)	0.087 (0.061)
- Number of brothers	-0.058** (0.026)	-0.034 (0.027)	-0.061** (0.024)	-0.027 (0.026)	-0.046** (0.023)	-0.031 (0.023)
- Number of sisters	-0.043 (0.029)	-0.026 (0.033)	-0.043 (0.029)	-0.031 (0.034)	-0.030 (0.028)	-0.027 (0.031)
<i>Family disadvantage</i>						
- Migrated before 8 years old			0.102* (0.059)	-0.071 (0.065)	0.051 (0.058)	-0.100 (0.063)
- Indigenous background			0.077 (0.047)	-0.002 (0.077)	0.035 (0.049)	0.025 (0.068)
- One parent absent (8 years old)			-0.099 (0.069)	-0.101 (0.072)	-0.084 (0.072)	-0.123* (0.067)
- Born to a teenage mother			-0.028 (0.077)	0.147* (0.081)	-0.045 (0.078)	0.140* (0.083)
- Caregiver's partner gets drunk at least once a week (8 years old)			-0.065 (0.060)	-0.040 (0.072)	-0.047 (0.063)	-0.028 (0.069)
<i>Predicted skills (15 years old)</i>						
- Cognitive					0.118*** (0.018)	0.169*** (0.039)
- Non-cognitive					0.058** (0.029)	0.021 (0.023)
Number of observations	341	294	341	294	341	294

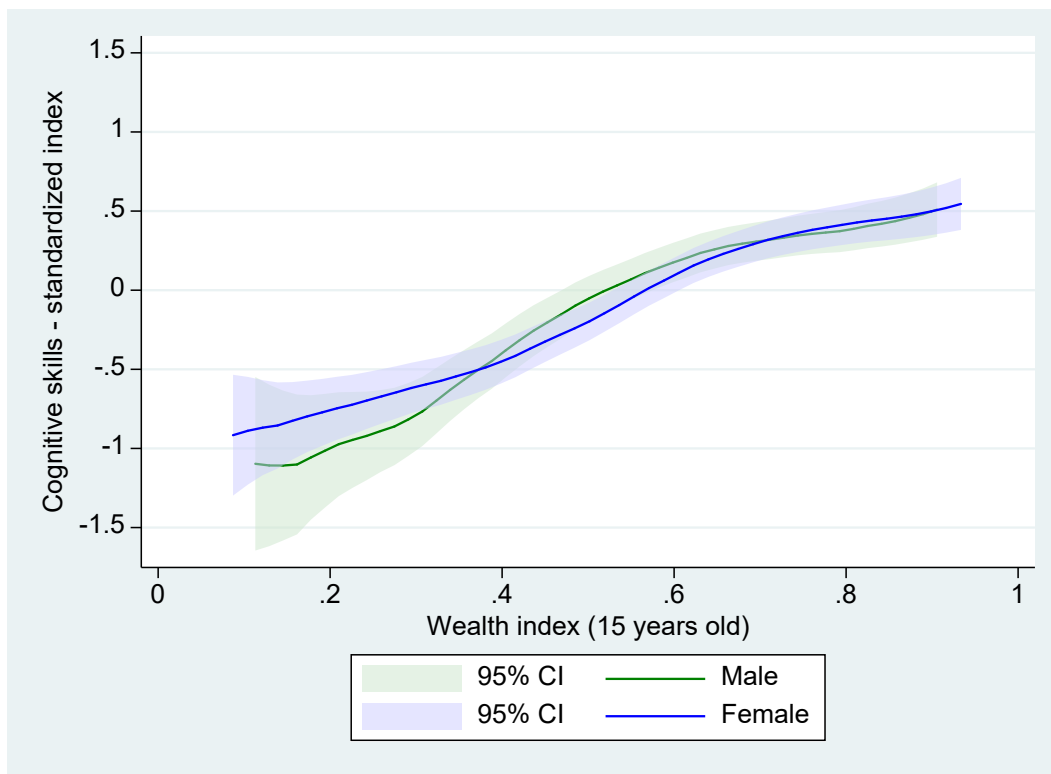
Notes: Clustered standard errors in parentheses. * p < 01, * p < 005, *** p < 001. The data used for the regressions comes from the older cohort of the Young Lives study (Peruvian sample).

Table 4: Structural model of enrollment in Higher Education - mechanisms

	A		B		C	
	Male (1)	Female (2)	Male (3)	Female (4)	Male (5)	Female (6)
<i>Wealth index (15 years old)</i>						
- Middle tercile	-0.108 (0.069)	0.188* (0.105)	-0.069 (0.096)	0.123 (0.096)	-0.070 (0.095)	0.126 (0.097)
- Top tercile	0.059 (0.063)	0.282** (0.117)	0.108 (0.096)	0.198 (0.120)	0.098 (0.092)	0.200* (0.121)
<i>Predicted skills (15 years old)</i>						
- Cognitive	0.117*** (0.018)	0.170*** (0.038)	0.122*** (0.018)	0.166*** (0.040)	0.121*** (0.017)	0.167*** (0.039)
- Non-cognitive	0.056* (0.029)	0.021 (0.022)	0.055* (0.029)	0.026 (0.023)	0.053* (0.030)	0.026 (0.022)
<i>Credit constrained</i>						
	-0.041 (0.062)	0.012 (0.056)			-0.048 (0.064)	0.013 (0.055)
<i>Higher ed. institution > 60 min</i>						
			0.113 (0.137)	-0.193** (0.087)	0.117 (0.135)	-0.195** (0.087)
Controls for standard regressors (household and child characteristics) and family disadvantage indicators						
	Yes		Yes		Yes	
Number of observations	341	294	341	294	341	294

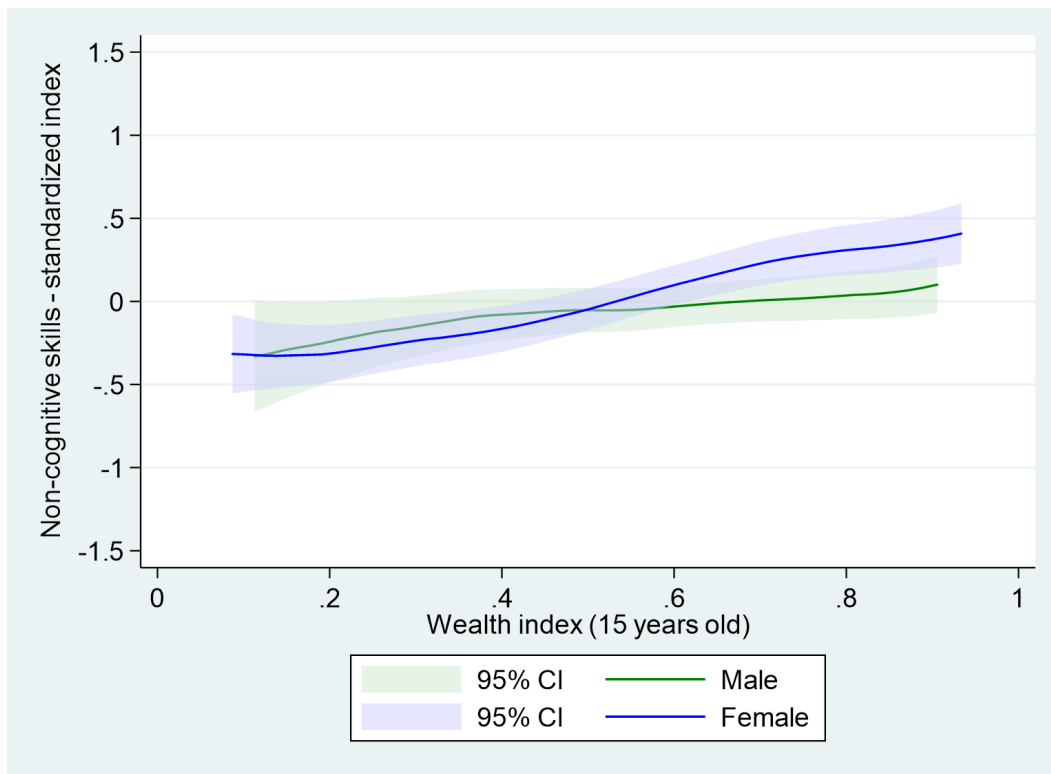
Notes: Clustered standard errors in parentheses. * $p < 01$, * $p < 005$, *** $p < 001$. All specifications control for: caregiver's education, rural location of the household, height-for-age z-score, family structure and family disadvantage. The data used for the regressions comes from the older cohort of the Young Lives study (Peruvian sample).

Figure 1: Wealth index and cognitive skills during adolescence, by gender



Notes: The figure plots a polynomial smoothing of our indicator of latent cognitive skills (estimated through exploratory factor analysis) on the index of household wealth during adolescence (Round 3 of the Young Lives study).

Figure 2: Wealth index and non-cognitive skills during adolescence, by gender



Notes: The figure plots a polynomial smoothing of our indicator of latent non-cognitive skills (estimated through exploratory factor analysis) on the index of household wealth during adolescence (Round 3 of the Young Lives study).

Appendix Table 1: Variable selection for the estimation of latent factors

	Survey Round			Component
	1	2	3	
A. Cognitive skills				
Writing skills	x	x		Measures the child's ability to write. 1 = "does not know how to write"; 2 = "writes with difficulty"; 3 = "writes without difficulty".
Numeracy skills	x			Measures the child's ability with numbers. 1 = "child identifies numbers correctly".
Reading skills	x			Measures the child's ability to read. 1-4 score, where 1 = "child cannot read" and 4 = "child reads without difficulty".
Raven test	x			Test measuring abstract reasoning (Rasch score)
PPVT test		x	x	Test of receptive vocabulary (Rasch score)
Mathematics test		x	x	Test measuring the child's mathematical ability (Rasch score)
Cloze test			x	Test of language skills (Rasch score)
B. Non-cognitive skills				
Pride index		x	x	Standardized item measuring the child's self-esteem.
Agency index		x	x	Standardized index measuring the child's self-efficacy or mastery of her own life.
Respect index		x	x	Standardized index measuring the child's overall evaluation of her own worth.
Trust index		x	x	Standardized index measuring the child's support networks.
C. Parental investments				
Child work	x	x		=1 if the child participated in any form of paid work during the last 12 months.
Help with household chores	x			=1 if the child helps with household chores on a regular basis
Frequency that the child sees her father	x			1-5 score, where 1 = "every day" and 5 = "never".
Relationship with parents		x		Index measuring the child's perception of the quality of her relationship with her parents.
Time spent studying		x		Time dedicated to studying by the child in an average day.
Time spent helping with household chores			x	Time dedicated to helping with household chores by the child in an average day.
Expenditure in children's clothes			x	Expenditure in children's clothes per child in the household
Expenditure in school items			x	Expenditure in school items per child in the household