

ARTICLE



Schooling, numeracy, and wealth accumulation: A study involving an agrarian population

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Abstract

Accumulating wealth is one of the main concerns for consumers. Higher education is widely associated with higher wealth, but the underlying reasons for this association remain unclear. Using data from a field study conducted with 218 adults in agrarian communities in Peru's Andean highlands, we explored the extent to which education, non-numeric fluid intelligence, crystallized intelligence, and numeracy skills were related to wealth. Wealth was measured using data on asset ownership (e.g., owning a fridge) and housing characteristics (e.g., toilet facilities). Structural equation modeling revealed that the level of schooling was associated with greater numeracy as well as greater non-numeric fluid and crystallized intelligence; only greater numeracy was associated with greater wealth. Our findings are consistent with the idea that education is linked with financial outcomes, at least in part, through the enhancement of cognitive skills, particularly numeracy that then leads to greater wealth accumulation.

1 | INTRODUCTION

The accumulation of financial wealth is one of the main concerns for individuals everywhere. Wealth is critical for people's well-being because it allows individuals to be economically secure, stable, and independent, and it creates opportunities for the next generation (Shapiro *et al.*, 2013). Moreover, wealth allows people to move forward by moving to better neighborhoods, investing in business, investing in the education of their children, and saving for retirement. Therefore, not accumulating enough wealth can profoundly hurt the well-being of individuals and their families. Given the central role of wealth in people's lives, it is important to obtain greater understanding of the major drivers behind wealth accumulation.

A number of studies now indicate that educational achievement is one of the main determinants of wealth. The main result is that people with higher education accumulate more wealth (Bernheim *et al.*, 2001; Ameriks *et al.*, 2003; Agarwal and Mazumder, 2013; Eccles *et al.*, 2013). Despite being very informative, these studies have not clearly proposed how school attendance produces such an effect. At the moment, little clarity exists concerning the psychological mechanisms that link more years of formal education with people's financial wealth. Knowing these mechanisms, however, may point toward better future interventions. In the present study and using data from an agrarian population, we investigated a possible mechanism. Specifically, we investigated whether exposure to schooling is associated with specific cognitive abilities (i.e., numeracy, non-numeric fluid intelligence, and crystallized intelligence), and whether these enhanced abilities are associated with greater wealth. The main purpose of the paper is to investigate which type or types of cognitive abilities matter for wealth accumulation.

The relationship between education and wealth has been difficult to disentangle. One possibility is that school attendance confers specific financial knowledge to make better financial decisions. However, the overall evidence suggests that the effect of superior financial education (i.e., the dissemination of knowledge) on financial outcomes is very limited unless the financial education occurs immediately before a specific financial decision (Mandell, 2006; Mandell and Klein, 2009; Fernandes *et al.*, 2014). Specifically, a meta-analysis showed that interventions to improve financial knowledge and financial abilities explain only 0.1% of variance in financial behaviors (Fernandes *et al.*, 2014). Therefore, financial knowledge may be a helpful but insufficient condition for making better finance-related decisions. Another explanation, based on the schooling-decision making model (Peters *et al.*, 2010; Baker *et al.*, 2015; Dieckmann *et al.*, 2015), is that formal education fosters cognitive abilities, which in turn provides individuals with enduring competencies to support better financial decisions. Below, we present evidence on the link between education, and cognitive abilities measured as fluid intelligence, crystallized intelligence, and numeracy. After that, we focus on the link between those abilities and wealth.

2 | MORE SCHOOL ATTENDANCE IS RELATED TO GREATER FLUID INTELLIGENCE, CRYSTALLIZED INTELLIGENCE, AND NUMERACY

Considerable evidence supports the view that formal education relates to increases in general intelligence (Ceci, 1991; Nisbett, 2009; Nisbett *et al.*, 2012), including domain-general fluid intelligence (defined as novel reasoning and logical thinking), crystallized intelligence (defined as verbal knowledge and long-term memory), and general intelligence (which is the combination of fluid and crystallized intelligence) (Horn and Cattell, 1966; Horn, 1988). For instance, it has been

shown that each additional month a student remains in school may increase the student's IQ score above what would be expected if the student had dropped out (Ceci, 1991, for a review of the historical literature). Similarly, it is generally recognized that most of individuals' mathematical knowledge only emerges with formal training. Although counting and simple arithmetic (e.g., number names) is sometimes taught by parents, more complex mathematical domains, such as algebra, geometry, calculus, and mathematical reasoning are commonly taught in school (Geary, 1994, Geary, 1995; see also Rozin, 1976). Moreover, the primary context in which individuals received sustained exposure to complex mathematical training is school (Ceci, 1991).

3 | GREATER NUMERACY AND HIGHER FLUID AND CRYSTALLIZED INTELLIGENCE ARE RELATED TO IMPROVED DECISIONS AND GREATER WEALTH

Higher numeracy has been linked to better decision making (Peters *et al.*, 2006; Reyna *et al.*, 2009), and to better financial decisions and better financial outcomes. For example, compared with less numerate individuals, individuals with greater numeracy skills are more likely to participate in financial markets and to invest in stocks (Christelis *et al.*, 2010; Almenberg and Widmark, 2011), more likely to plan for retirement (Lusardi and Mitchell, 2007; Lusardi and Mitchell, 2011), more knowledgeable when choosing a mortgage (Disney and Gathergood, 2011), less likely to default on loans (Gerardi *et al.*, 2010), and more likely to avoid predatory loans, pay loans on time, and pay credit cards in full (Sinayev and Peters, 2015). Research has also shown that numeracy is positively correlated with wealth (Banks and Oldfield, 2007; Smith *et al.*, 2010; Banks *et al.*, 2011; Lusardi, 2012; Estrada-Mejia *et al.*, 2016). These numeracy effects are robust to controls for sociodemographic variables and non-numeric measures of intelligence.

This previous research revealed that numeracy can significantly explain differences in wealth and other financial outcomes. However, what are the possible mechanisms that may link numeracy to higher wealth? First, one might expect the relation because better comprehension and integration of numeric information usually leads to more informed and therefore better decisions. Furthermore, numeracy extend beyond calculation abilities to color people's inclinations with respect to processing numeric and non-numeric information, how they perceive their world and understand the problems around them, and what strategies they use to solve those problems. Hence, numeracy may affect people's wealth, not only through increased comprehension of critical numeric information, but by influencing their economic preferences, reasoning and decision making processes, such that numeric information has a greater effect than non-numeric information on wealth accumulation.

Prior research found that people's numeracy is systematically related to time and risk preferences, and the level of motivation to attend to and elaborate upon numeric information (Peters, 2012). Individuals with higher numeracy tend to be less impatient, preferring larger delayed rewards over smaller immediate ones (Benjamin *et al.*, 2013). Patience is relevant to wealth accumulation because impatient people persistently report having lower savings (Howlett *et al.*, 2008; Hastings and Mitchell, 2011). Numeracy is also related to risk perceptions and preferences. More numerate individuals perceive less risk than the less numerate across a variety of domains including financial domains (Burns *et al.*, 2012), suggesting that they may be more willing to take greater risks in order to accrue greater wealth. In fact, individuals with higher numeracy appear more likely to take strategic risks, that is, to prefer a risky alternative when it is advantageous and to avoid it when it is not (Jasper *et al.*, 2013; Pachur and Galesic, 2013). We suspect people with

higher numeracy are more likely to use some kind of risk management strategy to cope with unexpected events, which in turn allows better planning and higher savings.

Finally, research has demonstrated that individuals with higher numeracy are better able than less numerate individuals to integrate multiple pieces of numeric information (Peters *et al.*, 2009), to have greater motivation to seek out and attend to numeric information (Lipkus and Peters, 2009), to remember numbers better (Garcia-Retamero and Galesic, 2011; Peters and Bjalkebring, 2015), and to draw more affective meaning from numbers (Peters *et al.*, 2006; Petrova *et al.*, 2014). We speculate that people with greater numeracy seek out and attend to these important numbers more, using them more effectively in their decision making.

Researchers have also studied the relationship of fluid and crystallized intelligence with financial outcomes. Li *et al.* (2015) revealed that both crystallized intelligence and fluid intelligence were associated with higher credit scores (high credit scores reflect a sustained ability to make good financial decisions over one's lifetime; Mester, 1997). Similarly, it has been suggested that people with greater crystallized intelligence (measures with domain-specific assessments of financial literacy) are more likely to accumulate and manage wealth effectively (Hilgert *et al.*, 2003; Banks and Oldfield, 2007; Banks *et al.*, 2011), invest in the stock market (Van Rooij *et al.*, 2011), and choose mutual funds with lower fees (Hastings and Tejeda-Ashton, 2008). Fluid and crystallized intelligence are thought to be linked to higher wealth through similar mechanisms to what we posit for numeracy. In particular, time and risk preferences have been found to vary with cognitive ability (Dohmen *et al.*, 2010; Li *et al.*, 2013). Specifically, higher cognitive ability is associated with lower risk aversion, and less impatience. As explained above, being more patient and taking more strategic risk has been associated with better financial decision making. However, none of these studies differentiated between non-numeric fluid intelligence, crystallized intelligence, and numeracy to attempt to disentangle the possible unique effects of the different constructs. Our study is unique in its attempt to do so.

4 | SCHOOLING-NUMERACY-INTELLIGENCE-WEALTH MODEL

On the basis of the findings presented above, we developed the model presented in Figure 1. In this model, exposure to schooling increases numeracy as well as non-numeric fluid and crystallized intelligence, which are, in turn, associated with greater wealth. We propose that greater non-numeric fluid intelligence, and crystallized intelligence and higher numeracy enable an individual to understand numbers related to wealth accumulation better and work with them

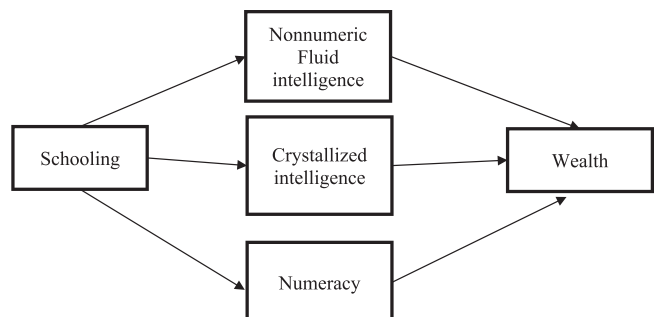


FIGURE 1 Conceptual model of the effect of formal education on wealth and the mediation of this effect by increased cognitive abilities

more effectively (Reyna *et al.*, 2009; Peters, 2012). Better comprehension and integration of numeric information usually leads to more informed and therefore better decisions.

5 | METHOD

In the study presented in this article, we tested our model in an agrarian population: the Quechua people from the highlands of Peru. The sample for this study was purposefully selected based on high levels of variation in educational attainment (i.e., years of schooling ranging between 0 and 16) and, conversely, high levels of homogeneity of *occupational structure* (i.e., 50% of the populations in these areas were subsistence-level farmers, and the remainder were employed in the local agrarian economy), *similar parental education* (i.e., 87% of the mothers and 73% of the fathers did not complete primary education), and *similar access to financial services* (i.e., financial institutions have very limited presence in this regions). This relatively homogeneous population provides natural control over many of the common sources of endogeneity that exist in developed countries. A major challenge to exploring the impact of formal education in Western countries is that most adults in developed nations have significant educational attainment and to a similar degree (e.g., finishing high school is a requirement in many developed countries today). Therefore, little variance exists among participants, which makes it challenging to separate the effect of schooling from the effects of intelligence and numeracy. Separating these effects is crucial to examining the factors' unique contribution.

5.1 | Sample

Participants were from the Ancash region of the Peruvian Andes. A door-to-door survey was conducted to recruit subjects, stratified by education attainment. Only heads of households or their partners were included, and we excluded participants who did not complete the numeracy test.¹ The final sample consisted of 218 adults. We present descriptive statistics of the sample in Table 1.

5.2 | Procedure

All instruments were administered in Spanish or Quechua (participants' native language). Instruments that were written originally in English were translated into Spanish and Quechua and then back translated into English. Interviews were conducted one-on-one, in Spanish or Quechua, in private homes or at village school buildings. Participants were compensated with household goods (e.g., sugar or pasta) and schools in participating villages were given educational materials.

5.3 | Measures

5.3.1 | Wealth index

The measurement of wealth is particularly challenging in developing countries where individuals have little or no access to financial services. In response, alternative measures based on

TABLE 1 Sample demographics
(*N* = 218)

Characteristic	<i>N</i> (%)
<i>Age cohort</i>	
30–39	69 (31.7)
40–49	77 (35.3)
50+	72 (33.0)
<i>Gender</i>	
Female	112 (51.4)
Male	106 (48.6)
<i>Mother tongue</i>	
Quechua	153 (70.2)
Spanish	65 (29.8)
<i>Residence</i>	
Urban (Small town)	128 (58.7)
Rural	90 (41.3)
<i>Married or cohabitating</i>	172 (78.9)

indicators of ownership of durable goods and housing characteristics have been developed (Filmer and Pritchett, 2001; Sahn and Stifel, 2003; Smits and Steendijk, 2014). Research has demonstrated that these alternative measures are as reliable as more conventional wealth measures (Montgomery *et al.*, 2000; Filmer and Pritchett, 2001). Therefore, wealth was assessed using one of these proven alternative methods, that is, measuring the quality and quantity of participant households' durables and housing. Household durables were measured with indicators of ownership of stereos, TVs, computers, stoves, refrigerators, bicycles, and communication devices (i.e., cell phone and/or landline). Housing quality was assessed with indicator variables for sources of drinking water (i.e., piped water vs. other sources), toilet facilities (i.e., flush toilet inside the house vs. no toilet or latrine outside the house), and household construction material (e.g., indicators of flooring quality). Hereafter, we will refer to the combination of household durables and housing characteristics as participants' assets.

To construct a wealth index, we follow the method proposed by Sahn and Stifel (2000, 2003). A factor analysis was conducted of the 14 different assets. Three assets (i.e., car, motorcycle, and radio) had factor loadings below the conventional level of 0.3, and were therefore excluded. A second factor analysis on the remaining 11 assets showed that only one component had an eigenvalue over Kaiser's criterion of 1. The scree plot also suggested retaining only one factor. Given the convergence of the scree plot and Kaiser's criterion, only one factor was retained for the final analysis. Last, total wealth scores were computed using a regression scoring method. Table 2 presents the factor loadings for the assets included in the final analysis and the percentage of participants who owned each of the assets.

5.3.2 | Numeracy

Numeracy was assessed using three questions targeting probabilistic reasoning and modified from a standard numeracy measure (Lipkus *et al.*, 2001). Items are in the form of mathematical

TABLE 2 Factor loadings and prevalence of assets included in the wealth index

Assets	Factor loadings	Prevalence %
<i>Housing quality</i>		
Cement floor versus earthen floor	.718	35.3
Indoor toilet facilities versus outdoor	.569	69.7
Piped water versus other sources of water	.344	87.2
<i>Household durables</i>		
Stove	.811	46.8
TV	.661	62.4
Fridge	.651	28.4
Stereo	.628	28.4
Computer	.622	17.9
Landline	.451	14.7
Cellphone	.436	65.6
Bicycle	.377	26.2

Note: Entries are factor loadings and the percentage of participants who own the asset.

problems with a unique correct response. Psychometric analyses using item response theory (IRT) methods revealed that only two items had acceptable discrimination and, therefore, only these two items were retained. The items read as follows and respondents answered the questions in the same order as presented below.

Item 1: Imagine you were going to buy a raffle ticket and you had three different raffles to choose from. In the first raffle, one out of every 100 people wins. In the second raffle, one out of every 1,000 people wins. In the third raffle, one out of every 10 people wins. Which raffle would you rather play?

Item 3: If the chance of winning a raffle is 10%, how many people would you expect to win out of 1,000?

The total resulting numeracy score was calculated using the difficulty and discrimination parameters estimated from the IRT analysis. Table 3 contains the four possible response patterns, their frequency of occurrence, and the corresponding total numeracy score. We rescaled the IRT scores by setting the minimum score to zero. Thus, participants who answered both questions wrong received a total score of zero. Higher scores indicate higher levels of numeracy. The reader might notice that participants answering item 3 correctly and item 1 incorrectly received a lower score than those answering item 1 correctly and item 3 incorrectly. In the IRT framework, this is possible because the scores are obtained by weighting the observed “response patterns” using the item parameters. The response pattern of answering a difficult question (item 3) correctly and an easy question (item 1) incorrectly is unlikely, thus resulting in a lower test score, because factors other than a person’s numeracy level are likely involved in explaining the response pattern. More details of the IRT model are reported in Appendix A.

5.3.3 | Education

Participants indicated the number of years of schooling completed.

TABLE 3 Response patterns for two numeracy items, frequencies of occurrence and corresponding numeracy score

Response pattern	Number of respondents	Item response theory numeracy score	Numeracy scores rescaled
Item 1 and Item 3 incorrect	66 (30.3%)	−0.79	0
Item 1 incorrect and Item 3 correct	18 (8.3%)	0.00	0.79
Item 1 correct and Item 3 incorrect	74 (33.9%)	0.05	0.84
Item 1 and Item 3 correct	60 (27.5%)	0.84	1.63

5.3.4 | Crystallized intelligence

Assessed using the Peabody picture of vocabulary test (PPVT; Dunn *et al.*, 1986). For each item, the facilitator presents a page with four pictures and then speaks a word describing one of the pictures. The participant is asked to point to or say the number of the picture that corresponds to the word.

5.3.5 | Non-numeric fluid intelligence

Assessed with four different instruments that have been psychometrically validated and are commonly employed in studies of cognitive ability. We conceptualized these four tasks as indicators of a latent construct, and we found that all measures were positively correlated (*Pearson correlations* = .25–.42, $p < .01$; see Table 5), as expected. The measures were the following:

Verbal fluency

Assessed with the COWAT (controlled oral word association test; Loonstra *et al.*, 2001), which requires participants to generate words within a category (e.g., animals) in a specified amount of time (60 s).

Working memory

Assessed with the backward digits task (Wechsler, 1981). In it, participants are presented with a series of numeric digits and are asked to repeat them back in reverse order. Note that this measure does include numbers but does not require participants to perform any numeric operations.

Planning

The Delis-Kaplan executive-function system tower test was used to measure participants' planning, strategy, working memory, and attention shifting abilities (Delis *et al.*, 2001). Using a board with three vertical pegs and five colored disks varying in size from small to large, the participants were asked to move the disks from a predetermined starting position to a specified ending position, where better solutions involve the fewest and most direct moves.

TABLE 4 Descriptive statistics for all measures included in the analysis ($N = 218$)

Characteristic	Mean	SD	Min	Max
Wealth	0	0.93	−1.28	1.77
Numeracy	0.79	0.62	0	1.63
Years of schooling	7.41	4.85	0	16
Non-numeric fluid intelligence				
<i>Verbal fluency</i>	16.58	4.81	6	31
<i>Working memory</i>	3.44	2.04	0	10
<i>Planning</i>	3.64	1.93	1	9
<i>Nonverbal reasoning</i>	5.54	1.97	0	9
Crystallized intelligence	73.74	12.47	11	89

Nonverbal reasoning

The Raven colored progressive matrices test was used to assess nonverbal reasoning about complexity (Raven *et al.*, 1998). In this task, the subject is presented with a series of pattern matrices (i.e., 2×2 , 3×3 , or 4×4) and asked to identify the missing element that completes each pattern.

5.3.6 | Control variables

Controls included gender, age, residence (i.e., small town, defined as 100 or more households clustered together, vs. rural), marital status (i.e., living with a partner vs. not), and mother tongue (i.e., Quechua versus Spanish). Table 4 shows the basic descriptive statistics for all measures.

5.4 | Analytic approach

First, a two-parameter logistic IRT model was used to examine the psychometric properties of the numeracy scale. Details about this model are reported in Appendix A. Second, we examined correlations between wealth and each of the potential predictors. Next, structural equation models (SEMs) were used to test the effect of educational attainment, numeracy, and non-numeric fluid and crystallized intelligence measures on wealth.² Unlike a regression analysis, the SEM approach allows us to model latent constructs that explicitly account for measurement error (e.g., the latent construct of fluid intelligence) and to include educational attainment as a simultaneous predictor of numeracy, non-numeric fluid intelligence, crystallized intelligence, and wealth. SEMs were estimated using Stata 13, and traditional criteria (e.g., Bayesian information criterion [BIC]; root mean square error of approximation [RMSEA]; likelihood-ratio goodness-of-fit tests) were used to compare alternative models and to assess fit (Raftery, 1995). In addition, in an attempt to quantify the strength of the evidence in support of one model over another, we used Raftery's (1995) rules of thumb for differences in BIC between Model A and Model B: weak evidence if BIC difference is between 0 and 2; positive evidence if BIC difference is between 2 and 6; strong evidence if BIC difference is between 6 and 10; and very strong

evidence if BIC difference is higher than 10. As an additional (primarily descriptive) illustration of the effect of numeracy on wealth, we also estimated the probability of holding each of the assets from the wealth index using a mixed-effects logistic regression model. Details of this model are presented in Appendix B. Last, to check robustness, we estimated a series of regression models and found similar results. These models are presented in Appendix C and Appendix D.

6 | RESULTS

6.1 | Descriptive analyses

Roughly half of the participants were female (51.4%), 79% were married or cohabitating, with a mean age of 44.8 years ($SD = 8.5$, range = 30–60 years), 58.7% lived in a small town, and 70.2% spoke Quechua as their first language. Participants had completed, on average, some middle school education ($M = 7.3$ years, $SD = 4.9$, Range = 0–16 years). About 12 % (11.9%) had no formal schooling, 34.9% had completed all or some elementary education (i.e., sixth grade or less), 34.9% had completed some or all of high school, and 18.3% had more than a high school education. An inspection of the pairwise correlations showed that more years of formal education, greater numeracy, and greater non-numeric fluid and crystallized intelligence were associated with greater wealth (Table 5).

6.2 | Structural equation models

We first tested different models using a SEM framework that explored whether numeracy can be modeled independently of the remaining non-numeric fluid intelligence latent variable.³ The first model (Model 1) included the four non-numeric fluid intelligence factors (i.e., verbal fluency, working memory, planning, and nonverbal reasoning) and numeracy as indicators of a single latent cognitive ability factor. In a second model (Model 2), we explored whether separating numeracy from the four fluid intelligence measures resulted in a better overall fit. A comparison of the fit indexes revealed that the second model, which treated numeracy as an independent construct from fluid intelligence, provided better fit to the data (comparative fit index: $CFI_{Model2} = 0.995 > CFI_{Model1} = 0.987$; tucker lewis index: $TLI_{Model2} = 0.985 > TLI_{Model1} = 0.974$; $RMSEA_{Model2} = 0.038 < RMSEA_{Model1} = 0.048$; $BIC_{Model2} = 3,979.456 < BIC_{Model1} = 4,340.484$).⁴ As a result, we modeled numeracy as a factor independent of fluid intelligence.

Figure 2 presents the initial model used to explore the simultaneous effects on wealth of education, non-numeric fluid intelligence, crystallized intelligence, and numeracy. The model provided an acceptable fit to the data ($CFI = 0.982$; $TLI = 0.975$; $RMSEA = 0.035$; $BIC = 10,112.890$). To find the most parsimonious model, nonsignificant pathways between predictors, control variables, and wealth were removed sequentially based on their respective significance levels. The final model, which also provided a good fit to the data ($CFI = 0.983$; $TLI = 0.977$; $RMSEA = 0.033$; $BIC = 10,103.316$) is presented in Figure 3. The two primary models were then compared to determine which model better fit the data. A likelihood-ratio test comparing the initial model and the final model, $\chi^2(2) = 1.2$, $p = .55$, revealed that the final model (Figure 3) is a more parsimonious model that fits as well as or better than the initial model (Figure 2). The same conclusion was achieved when comparing the BIC values for the two models ($BIC_{FinalModel} = 10,103.316 < BIC_{InitialModel} = 10,112.890$). The difference in BICs provided very strong evidence for the superiority of the final model (BIC difference = 9.574).



TABLE 5 Correlations between study variables (N = 218)

Variable	1	2	3	4	5	6	7	8	9	10	11	12
1. Wealth												
2. Numeracy	.47**											
3. Years of schooling	.65**	.51**										
4. Verbal fluency	.36**	.37**	.43**									
5. Working memory	.36**	.37**	.55**	.38**								
6. Planning	.19**	.30**	.29**	.28**	.41**							
7. Nonverbal reasoning	.41**	.44**	.48**	.36**	.41**	.25**						
8. Crystallized intelligence	.50**	.40**	.63**	.38**	.46**	.29**	.49**					
9. Age	.06	-.02	-.10	-.00	-.13*	-.18**	-.07	-.00				
10. Female	.00	.00	-.05	-.00	-.04	-.07	-.09	-.14*	-.09			
11. Quechua	-.41**	-.12*	-.25**	-.03	-.11	-.07	-.12	-.24**	-.02	.02		
12. Rural	-.63**	-.29**	-.45**	-.17**	-.27**	-.07	-.29**	-.39**	-.05	.02	.51**	
13. Married	.09	.08	.05	.14	.13*	.09	.07	.07	-.17**	-.21**	.06	.11

Notes: Variables were coded as follows: Gender (Male = 0, Female = 1); Mother tongue (Spanish = 0, Quechua = 1); Residence (Small Town = 0, Rural area = 1); Married or cohabitating (No = 0, Yes = 1).

* $p < .05$; ** $p < .01$.

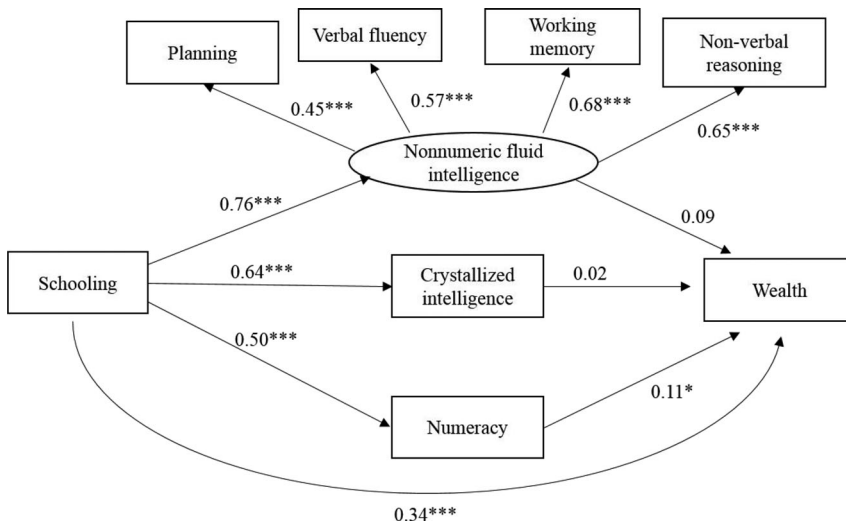


FIGURE 2 Structural equation modeling initial model. *Notes:* All parameter estimates are standardized regression coefficients. The following control variables were included as predictors of wealth (not displayed in figure): Age ($\beta = .12^{***}$), female ($\beta = .08^*$), lives in rural are ($\beta = -.35^{***}$), mother tongue Quechua ($\beta = -.12^{**}$), and married ($\beta = .13^{***}$). $^*p < .10$; $^{**}p < .05$; $^{***}p < .01$

In the final model, more education was a significant predictor of greater non-numeric fluid intelligence, crystallized intelligence, and numeracy. The direct effect of more formal education on greater wealth accumulation was also significant, but this pathway was attenuated as compared to the unadjusted education effect, thus suggesting a partial mediation. Greater numeracy, as predicted, remained a significant predictor of greater wealth after accounting for all other model effects. However, non-numeric fluid intelligence and crystallized intelligence were no longer statistically significant predictors of wealth.

We also tested several alternative models to examine the reverse of our hypothesis, specifically whether greater cognitive abilities predicted more schooling instead. We first considered whether higher numeracy was associated with more schooling; thus, we reversed the direction of the pathway between schooling and numeracy, without changing any other pathway. The reversed pathway was significant but resulted in a poor-fitting model (CFI = 0.911; TLI = 0.883; RMSEA = 0.077; BIC = 10,145.464). Similarly, we reversed the pathways between schooling and non-numeric fluid intelligence (CFI = 0.864; TLI = 0.825; RMSEA = 0.092; BIC = 10,196.32) and schooling and crystallized intelligence (CFI = 0.934; TLI = 0.914; RMSEA = 0.065; BIC = 10,128.004). These models also resulted in a worse fit. Finally, we reversed all pathways between schooling, and numeracy, non-numeric fluid intelligence and crystallized intelligence. In this model, numeracy and the two intelligence measures have a direct effect on schooling, and schooling has a direct effect on wealth. This model also resulted in a poor-fitting model (CFI = 0.800; TLI = 0.729; RMSEA = 0.118; BIC = 10,194.023). After drawing a comparison of the final model (Figure 3) and these alternative models using the BIC criteria, we concluded that the final model provided a better fit to the data than all of the alternative models (BIC final model = 10,103.316 < BIC all alternative models). Moreover, the difference in BICs revealed very strong evidence for the superiority of the final model compared to all alternative models (All BIC differences > 10). Additional robustness check can be found in Appendix C.

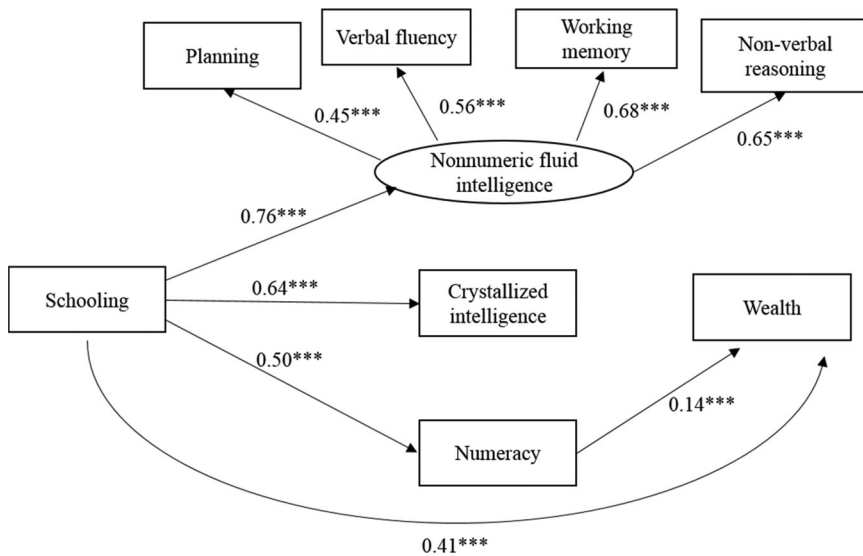


FIGURE 3 Structural equation modeling final model. *Notes:* All parameter estimates are standardized regression coefficients. The following control variables were included as predictors of wealth (not displayed in figure): Age ($\beta = .11^{***}$), female ($\beta = .07^{*}$), lives in rural area ($\beta = -.35^{***}$), mother tongue Quechua ($\beta = -.12^{**}$), and married ($\beta = .14^{***}$). $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$

As an additional illustration of the robustness of the effects, the probability of holding each of the assets from the wealth index was estimated using mixed-effects logistic regression models (Table 6). This model is an extension of a logistic regression model that considers the clustered structure of the data. In the present study, binary responses about the ownership of the different assets are nested within individuals. The probability of holding each of the assets was predicted using numeracy scores, non-numeric fluid and crystallized intelligence scores, and demographic variables. In addition, both the intercept and the slope coefficient for numeracy could vary across assets. In other words, we allowed the average probability of ownership to be different for each asset and we also allow the effect of numeracy, on the estimated probability, to be different for each asset. Probabilities were estimated for a typical sample respondent: a 44-year-old female, living in a rural area, married, whose mother tongue was Quechua, and with average scores for non-numeric fluid intelligence and crystallized intelligence. With the exception of owning a bicycle, the probability of holding each of the assets increased as numeracy increased. For instance, whereas the probability of having a stove was 48% for a participant with lower numeracy (1 *SD* below the mean), it was 89% for a highly numerate participant (1 *SD* above the mean). Likewise, whereas the probability of having a toilet facility inside the house was 87% for participants with lower numeracy, it was 96% for participants with higher numeracy. Probabilities were estimated with the model reported in Appendix B.

6.3 | Addressing endogeneity biases and an alternative path

As robustness checks, we estimate a series of regression models to test the relation between numeracy and wealth, controlling for several potential confounders. The results are very similar to those reported in the main text (Appendix C). However, two issues remain. First, a possible

TABLE 6 Predicted probability of holding household durables and housing quality indicators per numeracy level

Characteristics	−1 SD numeracy	Mean numeracy	+1 SD numeracy
<i>Housing quality</i>			
Floor made of cement versus earth	33.8	53.4	72.1
Toilet facilities versus no toilet	87.1	92.4	95.7
Piped water versus other	97.2	98.1	98.8
<i>Household durables</i>			
Stove	48.5	73.0	88.6
Fridge	23.0	40.9	61.6
Computer	15.8	24.1	35.1
TV	81.9	88.6	93.0
Stereo	31.0	43.9	57.7
Landline	16.0	19.9	24.6
Cellphone	88.1	90.4	92.3
Bicycle	48.5	41.9	35.7

Notes: Entries are estimated probabilities of holding the asset for a 44-year-old female, living in a rural area, married, whose mother tongue is Quechua, and with averages scores for non-numeric fluid intelligence and crystallized intelligence.

source of endogeneity may be the effect of an individual's family wealth (prior to that individual's schooling) on education and his or her own wealth. That is, participants with wealthy families may attain higher schooling and greater wealth (e.g., by inheriting parent's wealth). We do not have a precise measure for parental wealth. However, we estimated our final SEM model controlling for a proxy variable for parental wealth (whether the parents' mother tongue was Spanish or Quechua) and observed no change in the main findings. Model coefficients did not change in either sign or relative size (Appendix D). This proxy variable was chosen because studies have revealed that in these populations, individuals that speak fluent Spanish have better access to high-income jobs, can trade in bigger markets, and tend to be wealthier compared to individuals who only speak Quechua (MacIsaac and Patrinos, 1995; World Bank, 1999; López and della Maggiora, 2000).

A second factor may be that more educated individuals show greater postschooling effects on wealth. For example, people with more educational qualifications may have access to higher-paying occupations, resulting in higher wealth. However, job alternatives our participants held varied little (i.e., subsistence-level farmers or employees in the local agrarian economy) and controlling statistically for job type did not alter any coefficients (Appendix D). Overall, our data were more consistent with our final hypothesized model than with a model with the reverse pattern of causality.

7 | DISCUSSION

Education, non-numeric cognitive ability, and numeracy were associated with greater wealth accumulation (Banks and Oldfield, 2007; Smith *et al.*, 2010; Banks *et al.*, 2011; Lusardi, 2012; Estrada-Mejia *et al.*, 2016). However, the relative contribution of each of these factors to the

prediction of wealth is not well understood. Using data from a field study conducted in agrarian Quechua-speaking communities in Peru's Andean highlands, we explored the extent to which education, non-numeric fluid intelligence, crystallized intelligence, and numeracy skills were related to wealth. Wealth was measured using data on asset ownership (e.g., owning a bicycle or radio) and housing characteristics (e.g., type of toilet facilities). Results from SEM analysis revealed that exposure to schooling was associated with greater numeracy as well as greater non-numeric fluid and crystallized intelligence; the enhanced numeracy then was associated with greater wealth. For instance, an individual with higher numeracy (1 *SD* above the mean) was 38% more likely to own a fridge than an individual with equivalent demographic characteristics and intelligence but lower numeracy (1 *SD* below the mean). This result thus provides additional evidence in support of the schooling-decision making model (Peters *et al.*, 2010), which proposes that school attendance plays a key role in the development of cognitive abilities (Baker *et al.*, 2012; Nisbett *et al.*, 2012), which, in turn, supports better decision making (Peters *et al.*, 2010; Baker *et al.*, 2011; Dieckmann *et al.*, 2015). Specifically, these results are consistent with the idea that education has an effect on financial outcomes, at least in part, through the enhancement of cognitive skills, particularly numeracy, which then leads to greater wealth accrual.

The results of our study are consistent with the view of numeracy as a separable facet of intelligence (for similar findings, see Dehaene, 1997; Dehaene *et al.*, 2003). This point is important because it indicates that numeracy, and other forms of intelligence, can have different effects on people's judgments and decisions. Moreover, these results further suggest that researchers should investigate the potentially separable effects of different cognitive abilities on financial behaviors in addition to examining the effects of general intellectual ability. Getting a better understanding on where and how particular cognitive abilities play a role on financial decision making processes and wealth accumulation is essential to design interventions targeted to improve people's financial well-being. Experts in the field have suggested that one of the reasons to explain why financial education interventions may fail (Fernandes *et al.*, 2014) is that there is not enough focus on specific skills, such as the numeracy skills, needed to improve people's financial capability (Carpena *et al.*, 2011; Lusardi, 2012). Future work should focus on attempts to replicate these effects and to identify precisely how numeracy, and other cognitive abilities, impact financial behaviors in a range of contexts and populations.

We think our findings have also implications not only for the agrarian communities in Peru's Andean highlands but also for North American and Western European populations. Populations in developed countries face a relatively complex financial world, characterized by increasingly sophisticated financial products and services, and growing opportunities to personally interact with financial markets. Given that individuals in these contexts often have to deal with numerical information in the form of interest rates, exchange rates, risk incidence, base rates, and probabilities, we expect the effects of numeracy on wealth to be even stronger in these societies. Certainly, to make informed decisions in this complex financial context, it is essential for individuals to understand and use this numerical information.

One intriguing finding is that non-numeric fluid and crystallized intelligence were not significant predictors of wealth after accounting for the effects of numeracy and education. It is possible that numeracy was measured with less error than these two other cognitive abilities, which could have caused numeracy to be the only significant predictor. However, the measures used to assess participants' non-numeric fluid and crystallized intelligence have been used considerably in the literature and have shown to have excellent psychometric properties, arguing against this explanation. Another explanation for the nonsignificant association is that we

measured crystallized intelligence with a domain-general measure as opposed to a domain-specific measure. It has been suggested that the relationship between crystallized intelligence and financial outcomes is stronger when crystallized intelligence is measured with a domain-specific measure such as financial literacy (Li *et al.*, 2015). Further replication of this work may find that domain-specific measures of crystallized intelligence add additional power to the prediction of wealth.

7.1 | Limitations and future directions

This study has revealed a number of original findings. However, these results must be balanced against some limitations, all of which are related to data issues. First, as our current numeracy measure consisted of two items assessing probabilistic reasoning, we suggest that future research use a more robust measure. Although probabilistic reasoning has been shown to be an important predictor of wealth accumulation (Smith *et al.*, 2010; Estrada-Mejia *et al.*, 2016), a more robust assessment of numeracy might include a wider range of numeric skills. Moreover, the assessment of different numeric skills will allow future research to establish which kinds of numeric skills, if any, are most important for the accumulation of wealth. Thus, future work should focus on examining the role of different numeric abilities on wealth accumulation. In addition, recent research has demonstrated the potential importance of numeric confidence in interaction with objective numeric abilities for personal financial outcomes (Peters *et al.*, 2019). Another potential concern is that we do not control for inherited wealth in the analysis. Future studies could refine the wealth measure by including an indicator of whether the house was inherited. Individuals with financial family support might be less dependent on their own cognitive abilities for wealth accumulation.

Second, the data collected for this research are cross sectional and nonexperimental. Therefore, one has to be careful inferring causality between estimated effects. In the conceptual model, we propose that higher schooling leads to higher cognitive abilities, and higher cognitive abilities lead to higher wealth, possibly through better financial choices. However, our participants were not exogenously exposed to education. Hence, it is possible that the effect functions in the opposite direction, such that wealth is a causal determinant of education and cognitive abilities. To some degree, this issue is addressed by additional tests presented in Appendix D where we controlled for parental wealth. However, future work using instrumental variables that capture exogenous variation in education would be needed to strengthen our conclusions. Finally, we cannot account for the possible effect of an unobserved variable that could have jointly determined education and wealth. Additional factors, namely personality traits, health, tastes for asset accumulation, ability to delay gratification, among others, should be included in future research. Although these issues may affect the consistency of the estimators, we consider that for the purposes of obtaining the directions of the relationships, our results are sufficiently robust to be relevant to the literature.

8 | CONCLUSION

The present study revealed that the level of schooling was associated with greater numeracy as well as greater non-numeric fluid and crystallized intelligence; only enhanced numeracy was associated with greater wealth. Our findings are consistent with the idea that education has an

effect on financial outcomes, at least in part, through the enhancement of cognitive skills, particularly numeracy that then leads to greater wealth accumulation. Our results add to a growing literature highlighting the robust effect of education-enhanced numeracy on wealth. Even in a population with little to no access to traditional, numbers-heavy, financial mechanisms, numeracy appears to play a critical role in reasoning and decision making about one's finances. The present research is limited by its correlational nature, and future research should identify the causal mechanisms that underlie these effects and translate this knowledge into effective interventions to improve financial outcomes.

ENDNOTES

- ¹ A small number of participants did not complete the numeracy test. Unfortunately, we do not have information to explain why these participants did not complete the test. However, no differences existed in terms of sociodemographic variables between them ($n = 8$) and participants who did finish the numeracy measure ($n = 218$).
- ² According to the SEM literature, the minimum sample size adequate for analysis is generally 100 to 150 participants (Ding *et al.*, 1995; Kline, 2005). Our sample size of 218 participants conforms to that criterion.
- ³ Although substantive evidence has shown that numeracy is a separable facet of intelligence (Dehaene, 1997; Dehaene *et al.*, 2003), it is generally considered a component of fluid intelligence. We perform this test to validate that these two cognitive abilities can be modeled as independent constructs.
- ⁴ Higher CFI, higher TLI, lower RMSEA, and lower BIC values indicate better model fit.
- ⁵ For these analyses, a non-numeric fluid intelligence index was constructed. Scores for each independent measure were standardized and added together to give a compound measure.
- ⁶ For these analyses, a non-numeric fluid intelligence index was constructed. Scores for each independent measure were standardized and added together to give a compound measure.

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APPENDIX

A. IRT Analysis of the Numeracy Scale

Numeracy was assessed with three items modified from Lipkus *et al.* (2001) and designed to measure participants' probabilistic reasoning. Items are in the form of mathematical problems with a unique correct response. Before presenting the results of the IRT analysis, let us first explain why an IRT analysis was valuable for this research.

We conceptualize numeracy as a continuous variable that ranges from very low to very high. Although we cannot directly observe participants' numeracy, we can infer participants' ability

through their responses to a set of mathematical questions. Following a classical test theory approach, participants' numeric ability could be assessed by counting the number of correct responses. However, this approach is limited because items in the questionnaire may differ on their difficulty and on their capacity to discriminate between individuals with lower and higher numeracy. Consider, for example, the hypothetical responses of two participants, Rebeca and Pedro, who both answered only 1 of the questions correctly. Pedro, however, answered one of the "easy" questions correctly, whereas Rebeca correctly answered one of the "difficult" questions. Counting the number of correct responses would give Rebeca and Pedro the same score of one. Alternatively, weighting their responses by the difficulty and the discrimination capacity of the items would result in different total scores. IRT research has shown that weighted IRT scores better reflect the location of each of these participants along the numeric ability continuum (de Ayala, 2009).

Specifically, the difficulty parameter captures the location of the item along the numeracy continuum. In general, items located below zero are said to be "easy" and items above zero are "hard" (de Ayala, 2009). The discrimination parameter refers to how well the item differentiates between people with higher and lower numeric ability. Items with a high discrimination parameter are such that individuals with higher numeracy select the correct answer more often than individuals with lower numeracy.

A two-parameter logistic IRT model was estimated using the *irt* package for R. Each correct response is given a score of 1 and incorrect response a score of 0. Table A.1 presents the percentage of correct responses per item. The items read as follows and respondents answered the questions in the same order as presented below.

Item 1: Imagine you were going to buy a raffle ticket and you had three different raffles to choose from. In the first raffle, one out of every 100 people wins. In the second raffle, one out of every 1,000 people wins. In the third raffle, one out of every 10 people wins. Which raffle would you rather play?

Item 2: Imagine that 10 men and 20 women put their names on little pieces of paper and put them in a hat. If the papers were all mixed up, and you picked a name out of the hat without looking, do you think it would be the name of a woman or a man?

Item 3: If the chance of winning a raffle is 10%, how many people would you expect to win out of 1,000?

The item difficulty and the discrimination parameters are presented in Table A.1, Model A. An inspection of these estimates indicated that Item 2, with a negative discrimination parameter (Discrimination = -0.47) was inconsistent—participants with lower numeracy had a higher probability of answering the question correctly than those with higher numeracy. IRT

TABLE A.1 Percentage of correct responses to the numeracy items and parameters estimated with IRT models

Item	Correct responses	IRT model A		IRT model B	
		Discrimination	Difficulty	Discrimination	Difficulty
1	138 (61.6%)	1.67	−0.42	1.36	−0.47
2	57 (25.5%)	−0.47	−2.42		
3	78 (34.8%)	1.09	0.71	1.29	0.64

TABLE A.2 Response patterns for two numeracy items, frequencies of occurrence, and corresponding numeracy score

Response pattern	Number of respondents	IRT numeracy score	Numeracy scores rescaled
Item 1 and Item 3 incorrect	66 (30.3%)	−0.79	0
Item 1 incorrect and Item 3 correct	18 (8.3%)	0.00	0.79
Item 1 correct and Item 3 incorrect	74 (33.9%)	0.05	0.84
Item 1 and Item 3 correct	60 (27.5%)	0.84	1.63

theory suggests that items with negative discrimination parameters should be recoded or discarded (de Ayala, 2009). This item was not included in further analysis.

Next, the IRT model was estimated for the two items that remained. The difficulty and discrimination parameters are presented in Table A.1, column B. The difficulty parameters indicated that Item 1 (Difficulty = −0.47) was relatively easier than Item 3 (Difficulty = 0.64). On the other hand, the discrimination parameters revealed that Item 1 (Discrimination = 1.36) could differentiate better between participants located at different locations of the numeracy continuum than Item 3 (Discrimination = 1.29).

Total scores were calculated using the maximum likelihood estimation (MLE) approach. MLE considers whether the respondent answered each item correctly, and weight the answer by the item's difficulty and discrimination parameters (Embretson and Reise, 2000). As a result of combining information on the respondent's entire pattern of responses as well as the characteristics of each item, MLE can provide many more distinctions among respondents than just counting the number of correct responses (Van der Linden and Hambleton, 1997; Embretson and Reise, 2000). Table A.2 contains the four possible response patterns, their frequency of occurrence and the corresponding total numeracy score. We rescaled the IRT scores by setting the minimum score to zero. Thus, participants who answered both questions wrong received a total score of zero. Higher scores indicate higher levels of numeracy. The reader might notice that participants answering item 3 correctly and item 1 incorrectly received a lower score than those answering item 1 correctly and item 3 incorrectly. In the IRT framework, this is possible because the scores are obtained by weighting the observed "response patterns" using the item parameters. The response pattern of answering a difficult question (item 3) correctly and an easy question (item 1) incorrectly is unlikely, thus resulting in a lower test score, because factors other than a person's numeracy level are likely involved in explaining the response pattern.

B. Estimated Probabilities of Holding an Asset from the Wealth Index

The probability of holding each of the assets (house durables and housing characteristics) from the wealth index was estimated using a mixed-effects logistic regression model. This model is an extension of a logistic regression model that takes into account the clustered structure of the data. In the present study, binary responses about the ownership of the different assets are nested within individuals. The probability of holding each of the assets was predicted using numeracy scores, cognitive ability scores and demographic variables. In addition, both the intercept and the slope coefficient for numeracy were allowed to vary across assets. In other

words, we allow the average probability of ownership to be different for each asset and we also allow the effect of numeracy, on the estimated probability, to be different for each asset. Table B.1 and Table B.2 present the fixed-effects and random effects parameters, respectively.

Numeracy scores, cognitive ability scores,⁵ and age were mean-centered; other demographic variables were coded as follows: Gender (Male = 0, Female = 1); Mother tongue (Spanish = 0, Quechua = 1); Residence (Small Town = 0, Rural = 1); Married or cohabitating (No = 0, Yes = 1). Accordingly, probabilities were estimated for a *typical sample respondent*: a 44-year-old female, living in a rural area, married, whose mother tongue is Quechua, and with average scores for non-numeric fluid intelligence and crystallized intelligence. Probabilities were calculated as described below.

The probability that a typical respondent with an average score for numeracy would hold asset i can be described as, $(p_{\text{Holding asset } i}) = \frac{\exp(\beta_0 + u_{0i})}{[1 + \exp(\beta_0 + u_{0i})]}$, where β_0 refers to the intercept (fixed-effect), u_{0i} represents the random intercept for asset i , and $\exp$ refers to the exponential function $\exp(\beta_0 + u_{0i}) = e^{\beta_0 + u_{0i}}$ (Agresti, 2007). As an illustration consider the following example. The probability that the typical respondent owned a stove was equal to $(p_{\text{stove}}) = \frac{\exp(0.73 + 0.26)}{[1 + \exp(0.73 + 0.26)]} = 73\%$.

In a similar fashion, the probability that a typical respondent with high numeracy (1 SD above the mean) would hold asset i can be described as, $(p_{\text{Holding asset } i}) = \frac{\exp(\beta_0 + u_{0i} + \beta_1 + u_{1i})}{[1 + \exp(\beta_0 + u_{0i} + \beta_1 + u_{1i})]}$,

Fixed effects	β
Numeracy (mean centered) (β_1)	0.56* (0.23)
Fluid intelligence (mean centered)	0.10* (0.05)
Crystallized intelligence (mean centered)	0.03** (0.01)
Age (mean centered)	0.02 (0.01)
Female	0.20 (0.21)
Quechua	-0.54* (0.25)
Rural	-1.93** (0.26)
Married or cohabitating	-0.73** (0.26)
Constant (β_0)	0.73 (0.57)

TABLE B.1 Fixed-effects parameters of a mixed-effects logistic regression model used to predict the probability of holding an asset as a function of numeracy and other predictors

Note: Entries in the table are logistic regression coefficients (SD); The dependent variable is dichotomous and indicates whether asset i is held (1 = yes). Variables were coded as follows: Gender (Male = 0, Female = 1); Mother tongue (Spanish = 0, Quechua = 1); Residence (Small Town = 0, Rural area = 1); Married or cohabitating (No = 0, Yes = 1).

* $p < .05$; ** $p < .01$.

TABLE B.2 Random effects parameters of a mixed-effects logistic regression model used to predict the probability of holding an asset as a function of numeracy and other predictors

Assets ($N = 228$)	Random intercept (u_{0i})	Random slope for numeracy (u_{1i})
<i>Housing quality</i>		
Floor made of cement versus made of earth	−0.60	0.26
Toilet facilities versus no toilet inside the house	1.77	0.04
Piped water versus other sources of water	3.23	−0.14
<i>Household durables</i>		
Stove	0.26	0.50
Fridge	−1.10	0.29
Computer	−1.88	−0.02
TV	1.32	−0.01
Stereo	−0.98	0.00
Landline	−2.13	−0.29
Cellphone	1.51	−0.32
Bicycle	−1.06	−0.82

Note: Entries in the table are parameter estimates for the random effects.

where β_0 is the intercept (fixed effect), β_1 is the fixed effect for numeracy, u_{0i} represents the random intercept for asset i , and u_{1i} represents the random slope for numeracy for asset i . In our example, the probability that this respondent owned a stove was estimated to be $(p_{\text{stove}}) = \frac{\exp(0.73 + 0.26 + 0.56 + 0.50)}{[1 + \exp(0.73 + 0.26 + 0.56 + 0.50)]} = 88.6\%$.

Finally, the probability that a typical respondent with lower numeracy (1 SD below the mean) would hold asset i can be described as $(p_{\text{Holding asset } i}) = \frac{\exp(\beta_0 + u_{0i} - \beta_1 - u_{1i})}{[1 + \exp(\beta_0 + u_{0i} - \beta_1 - u_{1i})]}$, where β_0 represents the intercept (fixed effect), β_1 is the fixed effect for numeracy, u_{0i} represents the random intercept for asset i , and u_{1i} represents the random slope for numeracy for asset i . The probability of owning a stove was equal to $(p_{\text{stove}}) = \frac{\exp(0.73 + 0.26 - 0.56 - 0.50)}{[1 + \exp(0.73 + 0.26 - 0.56 - 0.50)]} = 48.5\%$.

C. Robustness Check—Regression Models

As robustness checks, we estimated a series of regression models to test the relation between numeracy and wealth, controlling for several potential confounders. The results are, however, very similar to those reported in the main text. The baseline model used numeracy, fluid intelligence,⁶ and crystallized intelligence as predictors of wealth. The demographic model added gender, age, residence, marital status, and mother tongue to the baseline model. The full model added education to the demographic model. Last, we repeat the full model controlling for whether the respondent was the head of the household or not.

Table C.1 shows the results of a set of three regression analyses modeling wealth. Model 1 (that included only numeracy, fluid intelligence, and crystallized intelligence) revealed that higher scores on all three variables were significant predictors of greater wealth ($b_{\text{Numeracy}} = 0.40$, $SD = 0.10$, $t = 4.10$, $p < .001$; $b_{\text{FluidI}} = 0.05$, $SD = 0.02$, $t = 1.99$, $p = 0.048$; $b_{\text{CrystallizedI}} = 0.02$, $SD = 0.01$, $t = 4.54$, $p < .001$). In Model 2, six control variables were included. Living in a small town as opposed to a rural area, speaking Spanish as opposed to Quechua, and being married or cohabiting as opposed to being single were all associated with higher wealth after controlling for numeracy, fluid intelligence, and crystallized intelligence. Again, all three variables were significant predictors of greater wealth ($b_{\text{Numeracy}} = 0.27$, $SD = 0.08$, $t = 3.34$, $p = 0.001$; $b_{\text{FluidI}} = 0.05$, $SD = 0.02$, $t = 2.40$, $p = 0.017$; $b_{\text{CrystallizedI}} = 0.01$, $SD = 0.005$, $t = 2.55$, $p < 0.012$) after controlling for these demographic controls. In Model 3, education (i.e., years of schooling) was included as a predictor. Of the three original measures, only numeracy remained a significant predictor of wealth after controlling for education ($b_{\text{Numeracy}} = 0.18$, $SD = 0.08$, $t = 2.26$, $p = 0.025$; $b_{\text{FluidI}} = 0.02$, $SD = 0.02$, $t = 0.86$, $p = 0.392$; $b_{\text{CrystallizedI}} = 0.002$, $SD = 0.005$, $t = 0.55$, $p = 0.585$). Next, one additional model (Model 4) controlling for whether the respondent was the head of the household showed no significant differences with Model 3. Finally, an

TABLE C.1 Linear regression analysis

	Model 1	Model 2	Model 3	Model 4
Numeracy	0.40** (0.10)	0.28** (0.08)	0.18* (0.08)	0.18* (0.08)
Fluid intelligence	0.05** (0.02)	0.05* (0.02)	0.02 (0.02)	0.02 (0.02)
Crystallized intelligence	0.02** (0.01)	0.01** (0.005)	0.002 (0.005)	0.003 (0.005)
Age		0.01 (0.01)	0.01** (0.005)	0.01** (0.005)
Female		0.15 (0.09)	0.15 (0.08)	0.19 (0.11)
Quechua		−0.26* (0.11)	−0.24* (0.10)	−0.24* (0.10)
Rural		−0.80** (0.11)	−0.67** (0.10)	−0.67** (0.10)
Married or cohabitating		0.28* (0.11)	0.30** (0.10)	0.34** (0.12)
Education			0.07** (0.01)	0.07** (0.01)
Head of the household				0.08 (0.12)
Constant	−2.07	−1.31	−1.29	−1.41
R^2	.35	.56	.62	.62
N	218	218	218	218

Note: Entries in the table are unstandardized betas (SD); DV = Wealth. Variables were coded as follows: Gender (Male = 0, Female = 1); Mother tongue (Spanish = 0, Quechua = 1); Residence (Small Town = 0, Rural area = 1); Married or cohabitating (No = 0, Yes = 1); Head of the household (No = 0, Yes = 1).

* $p < .05$; ** $p < .01$.

additional model including the interactions of each of the six control variables and numeracy revealed no significant interactions (all $p > .210$).

D. Robustness Check—SEMs Controlling for Parental Wealth and Participant Job Type

Figure D1 presents the results of the SEM analysis controlling for parents' mother tongue (i.e., Spanish or Quechua) as a proxy variable for parental wealth. Additionally, Figure D2 shows the findings of the SEM analysis controlling for participants' job type: subsistence-level

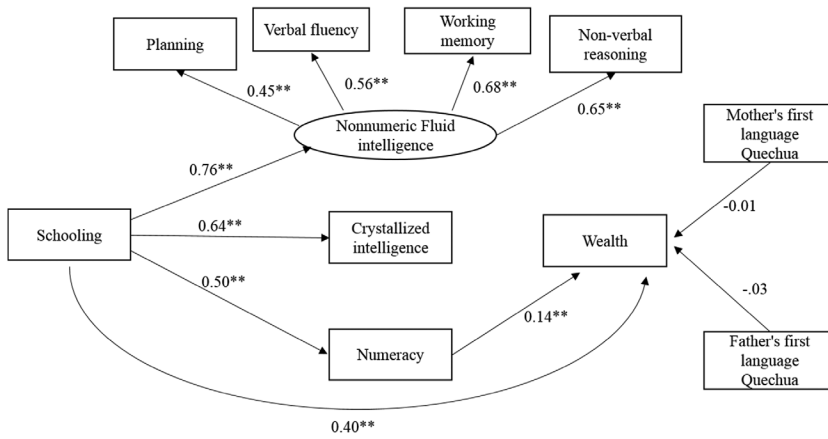


FIGURE D1 SEM model controlling for parental mother tongue (a proxy for parental wealth). *Note:* All parameter estimates are standardized regression coefficients. The following control variables were included as predictors of wealth (not displayed in figure): Age ($\beta = .11^{**}$), female ($\beta = .07^{+}$), lives in rural are ($\beta = -.36^{**}$), mother tongue Quechua ($\beta = -.12^{*}$), and married ($\beta = .14^{**}$). $^{+}p < .10$; $^{*}p < .05$; $^{**}p < .01$

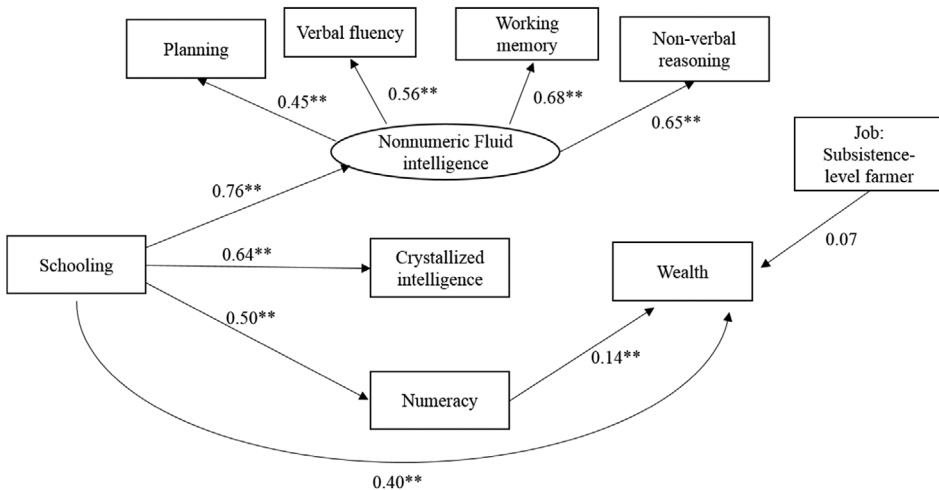


FIGURE D2 SEM model controlling for individuals' job type. *Note:* All parameter estimates are standardized regression coefficients. The following control variables were included as predictors of wealth (not displayed in figure): Age ($\beta = .10^{**}$), female ($\beta = .08^{+}$), lives in rural are ($\beta = -.38^{**}$), mother tongue Quechua ($\beta = -.13^{*}$), and married ($\beta = .13^{**}$). $^{+}p < .10$; $^{*}p < .05$; $^{**}p < .01$

farmers or employees in the local agrarian economy. Both analyses are consistent with the findings presented in the main text. More education was a significant predictor of greater fluid intelligence, crystallized intelligence, and numeracy. Greater numeracy remained a significant predictor of greater wealth after accounting for all other model effects. However, fluid intelligence and crystallized intelligence were no longer statistically significant predictors of wealth.