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PATIENCE, RISK-TAKING, AND HUMAN CAPITAL INVESTMENT ACROSS COUNTRIES*

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Patience and risk-taking—two preference components that steer intertemporal decision-making—are fundamental to human capital investment decisions. To understand how they contribute to international skill differences, we combine Programme for International Student Assessment tests with the Global Preference Survey. We find that opposing effects of patience (positive) and risk-taking (negative) together account for two-thirds of the cross-country variation in student skills. In an identification strategy addressing unobserved residence country features, we find similar results when assigning migrant students their country-of-origin preferences in models with residence country fixed effects. Associations of national preferences with family and school inputs suggest that both may act as channels.

Each release of international student assessment data such as the Programme for International Student Assessment (PISA) test brings both professional and popular discussions of the causes of national differences in test scores. Such differences attract widespread attention not only because of the national ranking aspect but also because they provide indices of skills that are important for individual earnings (Hanushek, Schwerdt *et al.*, 2015; 2017) and economic growth (Hanushek and Woessmann, 2012; 2015). Yet the underlying reasons for national differences in performance are not well understood. One often discussed but seldom analysed explanation involves cultural differences. This paper, relying on newly available measures of time and risk preferences across countries, establishes a clear case for linking skill investments to national preferences: international differences in student achievement are strongly related to international differences in patience and risk-taking.

Past research gives a mixed picture of the sources of test-score differences across countries (Hanushek and Woessmann, 2011; Woessmann, 2016b). Commonly available measures of educational resources such as aggregate spending, class size, and teacher characteristics explain little of existing score variation. By contrast, institutional features of school systems including test-based accountability, local autonomy, and private school competition provide some explanation of score differences. Additionally, the role of parents and families is consistently strong, although highly variable across countries. Yet, the deeper structural determinants of international

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differences in societal choices of schooling inputs and in the productivity with which they are converted into educational outcomes remain poorly understood.

We focus on the potential role of differences in intertemporal preferences across societies as constituting fundamental determinants of student achievement differences. Our conceptual framework—developed in greater detail in Online Appendix A—combines the usually separated literatures about optimal human capital investment and about education production functions in order to highlight the central nature of preferences underlying intertemporal decision-making. Moreover, while investment decisions are generally viewed from the individual perspective, many decisions on educational inputs—in particular about resources and school institutions—are taken at the group level rather than the individual level, making it hard to disentangle impacts of individual preferences from group preferences.[1]

Two components of national preferences are central to the relative valuation of net pay-offs in the present versus the future: time preferences (patience) and risk preferences (risk-taking). Human capital investment decisions take time to effectuate and even longer before any returns are realised. Just as the rewards for schooling investments require patience from the investor, national differences in patience may lead to national differences in educational outcomes.

The role of risk-taking is more ambiguous a priori. On the one hand, in line with the negative role of risk-taking stressed in the crime literature (e.g., Freeman, 1999), a preference for risk-taking may negatively impact the human capital production process. For example, it may induce students not to complete required homework even though they take the risk of being caught and reprimanded by parents or teachers. An increased willingness to take risk may therefore favour misbehaviour, reduce effort in studying and carry through to lower educational performance. On the other hand, consideration of various forms of school-completion and labour-market risks produces indeterminate predictions on how risk attitudes may affect human capital investment (Levhari and Weiss, 1974). For example, larger earnings variance in higher-educated occupations may give rise to a positive association between risk-taking and higher-education investment (e.g., Hartog and Diaz-Serrano, 2014), but lower unemployment risk (e.g., Woessmann, 2016a) may induce the opposite association.

Importantly, the intertemporal nature of human capital investment, its riskiness and the inherent interrelatedness of the two preference components (Halevy, 2008; Andreoni and Sprenger, 2012) imply that one cannot consider the impact of patience without simultaneously considering risk-taking, and vice versa.

Our empirical investigation is facilitated by the recent innovations in international preference measurement in Falk *et al.* (2018). Their Global Preference Survey (GPS) employs experimental means to validate survey instruments that can be used to collect systematic data on international differences in several preference parameters.

We combine the GPS data with PISA data on the educational achievement of close to two million students observed in seven waves from 2000 to 2018 across 49 countries. These data allow us to estimate international education production functions at the student level that bring out how country differences in national preferences affect the skills acquired by students.

Our baseline analysis finds a strong and competing relationship between the two preference components and students' educational achievement. Patience has a strong positive and risk-taking a strong negative association with test scores. The substantial positive correlation between the

[1] Following the literature (e.g., Guiso *et al.*, 2006; Alesina and Giuliano, 2015), we at times use 'culture' as shorthand for these group preferences. Obviously, however, culture is a very broad concept that has been given many different interpretations and goes far beyond the two intertemporal national preferences studied.

two preference components implies that looking at them individually leads to consequential understatement of their respective importance.

Together, the two aggregate preference measures account for two-thirds of the variation in country average scores. Thus, a significant portion of the cross-country variation in student achievement may be closely related to fundamental differences in national preferences. Consistent with a leading role of national cultures, the associations of the preference measures with individual achievement are much stronger for native students than for migrant students who moved into the school system from a different country. Moreover, the findings are stable across separate subjects (math, science and reading) and subsamples (OECD and non-OECD).

To explore the causal structure of these cross-country associations, we focus on migrant students in the PISA data. Across 48 residence countries, we observe the country of origin of over 80,000 migrant students from 58 countries of origin with preference data. Following Figlio *et al.* (2019), we assign migrant students the preference values of their country of origin and study the performance of migrant children from different origin countries observed in the same residence country. We include fixed effects for each residence country to separate the effects of cultural factors from potentially correlated effects of the education systems, economies, or other common features of the residence country.

Students from home countries with an aggregate one standard deviation (SD) higher patience perform about 90% of a SD better in math (equivalent to the learning gains of roughly three years of schooling), whereas students from home countries with one SD higher risk-taking perform about 30% of a SD worse (equivalent to roughly one year of schooling). Consistent with an intergenerational persistence of home-country preferences, results are larger for migrant students who do not speak the language of their current residence country at home. While this migrant analysis cannot rule out all potential biases, our results are insensitive to different country samples, subjects, genders, alternative preference measures, definitions of the migrant population, different amounts of student test-taking effort and several adjustments for the selectivity of migration—the most obvious threats to identification.

To investigate various channels through which national preferences might influence student achievement, we link them to the proximate inputs of the education production function in a final descriptive analysis. Patience is significantly positively correlated with family inputs, school inputs, and residual achievement differences (which likely combine productivity differences with unobserved inputs) across countries. Risk-taking is negatively correlated with family and residual inputs. Our results point to particularly important roles for family and residual inputs.

Our analysis of student achievement follows the recent literature investigating the influence of cultural factors on economic behaviour and outcomes (Guiso *et al.*, 2006; Alesina and Giuliano, 2015). With our migrant student analysis, we also contribute to this literature's focus on intergenerational transmission (e.g., Bisin and Verdier, 2011; Alesina and Giuliano, 2014). Past study of international student achievement has treated cultural factors largely as a source of possible bias in estimating the effects of proximate inputs in a cross-country setting (e.g., Hanushek and Woessmann, 2011; Woessmann, 2016b). Here we show the value of directly addressing the potentially more fundamental role of some cultural traits as underlying causes of achievement differences in their own right, explaining largely unanalysed elements of the nature of societal human capital formation. The large effects of national preferences are in line with the role of unobserved parental characteristics that De Philippis and Rossi (2021) find in cross-country achievement differences.

One central conceptual feature is combining the two artificially separated strands of human capital literature: optimal investment decisions and the educational production process for skill development. The human capital investment literature following Mincer (1958), Becker (1964), Ben-Porath (1967) and others has measured human capital by individuals' years of schooling, equating skill development directly to the time costs of the investment. Human capital investments are portrayed as an individual intertemporal optimising decision involving varying time commitments over the life cycle. For simplicity and tractability, this literature abstracts from any differences in skills obtained from time in school. The education production function literature, however, focuses on individuals' qualitative skill differences, generally looking at individuals with the same investment of school years but with different investment inputs (e.g., Hanushek, 1986). With some variations, the relevant skills are systematically related to inputs of the individual, the family and the public through various aspects of schooling. These two lines of research are in essence looking at the same issue—how human capital investment decisions translate into differences in economically relevant skills. Treating these lines of research together yields clear insights into the deeper forces affecting skill differences of individuals and nations.

We also contribute to the literatures on time preferences (e.g., Sutter *et al.*, 2013; Golsteyn *et al.*, 2014; Figlio *et al.*, 2019), risk preferences (e.g., Levhari and Weiss, 1974; Castillo *et al.*, 2018) and their interrelatedness (e.g., Halevy, 2008; Andreoni and Sprenger, 2012; Castillo *et al.*, 2019; 2020). Consistent with the associations of preferences with individual outcomes, our results show that patience and risk-taking have important effects on countries' human capital investment. At the country level, our analysis also relates to work on long-run comparative development (e.g., Galor and Özak, 2016; Sunde *et al.*, 2021) and immigrants (e.g., Abramitzky and Boustan, 2017).

The next section describes the data. Section 2 develops the baseline estimates of the relationship of preferences and human capital across nations. Section 3 delves deeper into the causal structure using the analysis of migrants. Section 4 explores the association of patience and risk-taking with proximate input factors as possible channels. Section 5 concludes.

1. Data

Our analysis combines international data on student achievement (Subsection 1.1) and on preferences (Subsection 1.2). Details are found in Online Appendix B.

1.1. *The Programme for International Student Assessment*

The Organisation for Economic Co-operation and Development (OECD) has conducted the PISA test since 2000. PISA assesses achievement in math, science and reading of random samples of 15-year-old students on a three-year cycle (OECD, 2019), providing repeated cross-sectional data representative in each country-by-wave cell. PISA also elicits background information on students and schools that we use as controls and as measures of channels.

Over the seven waves of PISA testing, 2000–2018, a total of 86 countries participated at least once (see Table 5 in the Online Appendix for details of all samples). Our baseline cross-country analysis considers the subset of 49 countries that are also covered by the GPS, using achievement data from a total of 1,992,276 students from 263 country-by-wave observations.

In our migrant analysis, we include migrant students in any residence country as long as PISA identifies the country of origin and home-country GPS data are available. (The entire 2000 PISA wave drops out because of missing information on students' country of origin.) We observe

80,398 migrant students (and up to 145,506 in a wider definition) from 58 countries of origin located in 48 residence countries.

In the different parts of our analysis, we use data from a total of 86 countries, 71 of which participated in PISA and 64 of which have GPS data.

1.2. *The Global Preference Survey*

The newly available Global Preference Survey (GPS) provides scientifically validated, high-quality data on several preference parameters collected from representative samples in 76 countries (Falk *et al.*, 2018).[2] Using probability-based sampling, the GPS covers around 1,000 respondents in each country surveyed in 2012. We collapse the GPS data to the country level to construct one representative measure for each preference parameter per country. In total, we use GPS data from 64 countries—49 countries in the baseline cross-country analysis and 58 as countries of origin in the migrant analysis.

The GPS measures preferences in six domains: patience and risk-taking (the two preference components underlying intertemporal decision-making that are our main focus here) plus positive reciprocity, negative reciprocity, altruism and trust. The underlying survey items were selected in an *ex ante* validation exercise based on their ability to predict incentivised choices in a controlled laboratory setting. Patience and risk-taking are each measured by a combination of one qualitative survey question and one hypothetical choice scenario, which are then combined into a single preference measure using weights from the validation procedure.

Larger values of patience mean that the individual is more likely to accept deferred gratification. Larger values of risk-taking mean that the individual is more likely to take risky outcomes compared to certain outcomes. We z-standardise the GPS measure of each preference domain in our respective analytical sample and collapse standardised preference measures to the country level. Consistent with the interrelation emphasised in the behavioural literature, there is a strong positive correlation between patience and risk-taking in the GPS data of 0.358 at the country level (see Figure 2 in the Online Appendix).

2. Patience, Risk-Taking, and Student Achievement Across Countries

This section provides a description of the association of student achievement with patience and risk-taking across countries. It guides our analysis of the causal structure of the cross-country associations in Section 3.

2.1. *Empirical Model*

Our empirical approach contrasts with most empirical investigations of educational production functions that include a long list of possible variables in order to soak up potential impacts of families, schools, institutions, and cultural traits. Being interested in more fundamental

[2] Because the GPS provides scientifically validated preference measures from representative samples for a large set of countries, it has important advantages, discussed in Online Appendix B.2, over common alternative international datasets with proxies for national preferences such as the World Values Survey (WVS) and the Hofstede (1991) data. Correlations of our measures of intertemporal preferences with these alternatives and with the remaining GPS preferences are found in Table 7 in the Online Appendix. Studies analyzing PISA data in conjunction with WVS data include Mendez (2012) and Cordero et al. (2018); Studies analyzing PISA data in conjunction with Hofstede data include Figlio et al. (2019) and Breton (2021).

determinants of educational achievement across countries,[3] we employ a parsimonious specification of an education production function (Equation 1) that models the output of education as centrally determined by national preferences:

$$T_{ict} = \beta_1 Patience_c + \beta_2 Risk_c + \alpha_1 \boldsymbol{B}_{ict} + \mu_t + \varepsilon_{ict}, \tag{1}$$

where achievement T of student i in country c at time t is a function of the two preference components of the country, a parsimonious vector of control variables $\boldsymbol{B}$ (student gender, age, and migration status), and an error term ε_{ict}. Fixed effects for test waves μ_t account for average changes over time along with any idiosyncrasies of the individual tests. Our coefficients of interest are β_1 and β_2 which characterise the relationship between the two preference components of a country's society—patience and risk-taking—and student achievement.

To account for the country-level nature of the main treatment variables, we cluster standard errors at the country level throughout. All regressions are weighted by students' sampling probabilities within countries and give equal weight to each country. In our analysis, original PISA scores are divided by 100 to convert achievement into standard deviations.

2.2. *Results of the Baseline Analysis*

Results of the baseline model indicate important and intertwined roles of patience and risk-taking in international student achievement. Table 1 shows our baseline analysis of the association of student math achievement with patience and risk-taking across countries. When entered individually, there is a strong significant positive association of student achievement with patience (column 1) and a weaker, marginally significant negative association with risk-taking (column 2). Strikingly, both associations become much stronger (in absolute terms) and statistically highly significant when the two preference components are considered together (column 3), highlighting the importance of accounting for their interrelatedness. A one SD increase in patience is associated with a 1.23 SD increase in student achievement, whereas the same increase in risk-taking is associated with a 1.24 SD decline in student achievement. Conditioning on the other component is particularly relevant for risk-taking: that part of the variation in risk-taking that is unrelated to patience has a strong negative association with student achievement.[4]

The results on patience and risk-taking are hardly affected when taking measures of other preference domains into account (column 4). In fact, none of the other four GPS measures—positive reciprocity, negative reciprocity, altruism and trust—is quantitatively or statistically significantly associated with student achievement across countries. Thus, the preference components directly linked to intertemporal decision-making, rather than other preference domains, appear most relevant for educational achievement.

The interrelationship of the intertemporal preference components and achievement is depicted graphically in Figure 1. The upper panel shows simple bivariate scatterplots between average PISA math scores (pooled across waves) and the GPS measures of patience (left) and risk-taking

[3] Moreover, to the extent that proximate inputs such as family inputs, school resources, and institutional features are themselves the outcomes of intertemporal choice decisions, they are bad controls in a model depicting the overall effect of national preferences on student achievement (see Online Appendix A.2). Section 4 provides an analysis of these proximate inputs as potential channels of the impact of national preferences.

[4] Results are very similar for girls and boys, although the (absolute) estimate for risk-taking is slightly smaller for girls (columns 1 and 2 of Table 8 in the Online Appendix). An interaction term between patience and risk-taking does not enter the model significantly (not shown).

Table 1. *National Preferences and Student Achievement across Countries: The Intertwined Roles of Patience and Risk-taking.*

	Full sample						Controls for test-taking effort	
	(1)	(2)	(3)	(4)	Natives (5)	Migrants (6)	(7)	(8)
Patience	0.917***		1.226***	1.186***	1.296***	0.702***	1.176***	1.117***
	(0.127)		(0.132)	(0.123)	(0.133)	(0.172)	(0.124)	(0.121)
Risk-taking		−0.482*	−1.241***	−1.314***	−1.320***	−0.370	−1.200***	−1.141***
		(0.261)	(0.184)	(0.219)	(0.189)	(0.225)	(0.173)	(0.164)
Positive reciprocity				0.036				
				(0.226)				
Negative reciprocity				0.315*				
				(0.175)				
Altruism				−0.230				
				(0.188)				
Trust				−0.048				
				(0.152)				
Item non-response							−3.148***	−2.873***
							(0.158)	(0.151)
Item non-response (country mean)								−4.308***
								(1.046)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,992,276	1,992,276	1,992,276	1,992,276	1,751,822	192,736	1,992,276	1,992,276
Countries	49	49	49	49	49	49	49	49
R^2	0.134	0.042	0.198	0.213	0.214	0.078	0.246	0.251
Difference between subsamples								
Patience					−0.594***			
					(0.149)			
Risk-taking					0.950***			
					(0.242)			

Notes: Dependent variable: PISA math test score in all PISA waves 2000–2018. Least squares regression weighted by students' sampling probability. Item non-response refers to the share of questions not answered in the student background questionnaire following the achievement test. Control variables: student gender, age, and migration status; imputation dummies; and wave fixed effects. Robust standard errors adjusted for clustering at the country level in parentheses. Significance level: ***1%, **5%, *10%. Data sources: PISA international student achievement test, 2000–2018; Falk *et al.* (2018).

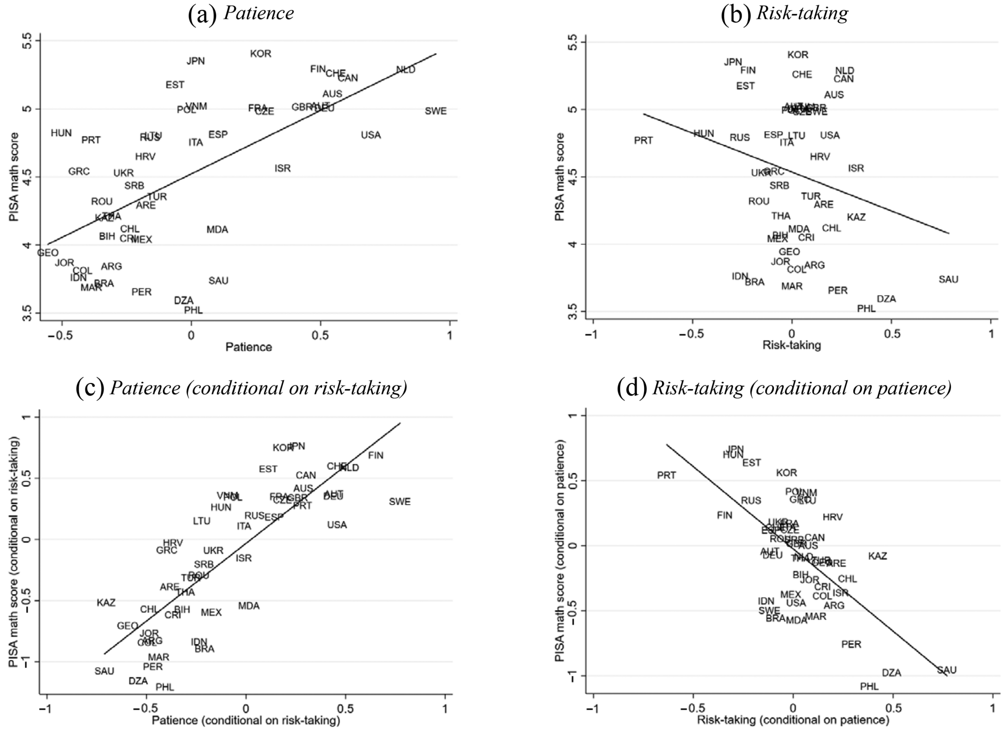

Fig. 1. *Patience, Risk-taking, and Student Achievement Across Countries.*
Notes: PISA math score: average student achievement, 2000–2018. The added-variable plot in the lower left panel is created by first regressing both variables (math achievement and patience) on risk-taking. The residuals of the two regressions are then plotted against each other. These residuals represent the part of the variation in both variables that cannot be accounted for by risk-taking, assuring that risk-taking does not drive the depicted association. This exercise is numerically equivalent to regressing math achievement on patience and including risk-taking as a control variable. The equivalent procedure is used in the lower right panel. Data sources: PISA international student achievement test, 2000–2018; Falk *et al.* (2018).

(right) at the country level.[5] There is a strong positive association of student achievement with patience and a weaker and less precise negative one with risk-taking. At the country level, the R^2 of the underlying regressions suggest that patience alone accounts for 40.9% of the cross-country variance in achievement, whereas risk-taking alone accounts for only 6.2%. Both associations become much stronger and more precise when conditioning on the respective other preference component in the lower panel. The two preference components together account for two-thirds of the variance in average student achievement across countries ($R^2 = 0.672$). Interestingly, this is substantially larger than the sum of explained variance accounted by the two measures separately, underscoring the off-setting interplay of the two intertemporal preference components. The figures also show that the overall associations are not driven by any strong outliers.

If cultural traits are driving the achievement results, one would expect the residence country culture to be less important for migrants whose parents are less steeped in that culture and whose

[5] Results are almost identical when estimating the PISA scores as country fixed effects in (1) that includes control variables (but not patience and risk-taking; results available upon request).

exposure to the new culture is less. When we look separately at native students and migrants, we find a much stronger role of residence country preferences for native students than for migrant students.[6] Among native students, a one SD increase in patience is associated with 1.30 SD higher achievement, and the same increase in risk-taking is associated with 1.32 SD lower achievement (column 5 of Table 1). By contrast, among students with a migrant background the association is much lower (0.70 SD) for patience and loses statistical significance (at 0.37 SD) for risk-taking (column 6). Both differences are statistically significant.

The difference in results between students with and without migration background is in line with a leading role of cultural traits as deep determinants of student achievement rather than other unobserved schooling factors of a country. It also motivates our migrant analysis below that considers the cultural traits of the migrant students' countries of origin.

2.3. *Robustness Analysis*

One interpretational concern with low-stakes achievement tests such as PISA is that they might not only measure students' cognitive skills but also their effort on the test itself which in turn may depend on students' conscientiousness, intrinsic motivation, and other related skills (e.g., Borghans and Schils, 2012; Akyol *et al.*, 2018; Gneezy *et al.*, 2019). Among a number of measures of students' test-taking effort derived for the 2009 PISA wave, Zamarro *et al.* (2019) find that the extent of item non-response (the share of unanswered questions) in the student background questionnaire that follows the actual achievement test explains the largest share of cross-country variation in test scores. We construct this measure for all PISA waves to test whether the strong association of the intertemporal preferences with PISA achievement partly reflects lower test-taking effort among less patient and more risk-taking students. Indeed, lower patience and higher risk-taking do significantly predict lower test-taking effort (higher item non-response on the background questionnaire) both at the individual and country level (not shown), validating a cultural component of test-taking effort.

While test-taking effort is relevant for overall test achievement, it does not alter the results for the two preference components. Individual students' item non-response rates on the background questionnaire negatively predict achievement on the math test (column 7 of Table 1). But the coefficients on patience and risk-taking hardly change. The same is true when we additionally control for average item non-response of the country (column 8). This is despite the fact that item non-response has substantial quantitative relevance. At the country level, the coefficient estimate suggests that going from the country with the lowest (0.010) to the highest (0.108) average item non-response decreases the average PISA score by 0.42 SD. Thus, while test-taking effort appears relevant in low-stakes test taking, it does not alter conclusions about the more fundamental preference-achievement nexus considered here.

Additional robustness analyses described in Online Appendix C show that qualitative results are very similar for OECD and non-OECD countries, for achievement in science and reading, and when restricting the analysis to the first PISA wave after the GPS observations. The Online Appendix also shows results for the alternative preference measures of WVS and Hofstede.

[6] Students are classified as migrants if both parents were born abroad. The migrant analysis in Section 3 shows that our findings are insensitive to alternative definitions of the migrant population.

3. Exploration into Causality: Migrant Analysis

An obvious concern with the cross-country regressions is that a country's national preferences are likely correlated with other omitted country characteristics, such as legal or economic factors, that affect human capital investments. While some of the variation in these country factors may be the outcome of the national preferences and thus constitute channels rather than omitted variables, there may also be independent variation that happens to be associated with the national preference measures. For instance, a culture of patience might foster the economic development in a country more broadly, making it impossible to distinguish whether a positive association between patience and student achievement is due to patience per se or to better well-being. To address concerns about the causal interpretation of the baseline analysis, we explore an identification strategy that analyzes cultural differences among migrants.

3.1. *Empirical Model*

If patience and risk-taking truly are cultural factors that affect educational investment decisions, migrants should retain some influence of the culture of their home countries. If we compare achievement across migrant children from home countries with different preferences who attend school in the same country of residence, we break the link between the cultural traits and elements of the schools, institutions, and environments of the country of schooling—something that cannot be done for natives. Following similar applications in Carroll *et al.* (1994), Giuliano (2007), Fernández and Fogli (2009), and Figlio *et al.* (2019), we estimate regressions of the following form:

$$T_{ioct} = \delta_1 \, Patience_o + \delta_2 Risk_o + \gamma_1 \boldsymbol{B}_{ioct} + \theta_c \times \mu_t + \varepsilon_{ioct}, \tag{2}$$

where T is achievement of migrant student i from country of origin o observed in residence country c at time t. $Patience_o$ and $Risk_o$ are the cultural traits measured in the country of origin.

The specification includes residence country fixed effects θ_c to remove all common economic, institutional, and schooling factors for each residence country. We pool the data across residence countries but only use variation within each residence country and not cross-country variation to estimate the preference impacts. In fact, our specification controls for a full set of residence country-by-wave fixed effects $\theta_c \times \mu_t$ which account for wave-specific differences across countries. Standard errors are clustered at the country-of-origin level.

We begin with a rather narrow definition of migrants, including only students with parents who are both born in a different country than the testing country. We assign first-generation migrant students their country of birth and second-generation migrant students the country of origin of their father. Across all PISA waves, there are 80,398 first- and second-generation migrants from 58 countries of origin with GPS data observed in 48 residence countries.

3.2. *Results of the Migrant Analysis*

The migrant analysis confirms the strong positive effect of patience on student achievement from the baseline analysis, as well as a significant negative effect of risk-taking, albeit of smaller magnitude compared to its baseline estimate and to the effect of patience. Table 2 reports the main regression results for the migrant analysis based on (2). All regressions include 180 fixed effects for each residence country by wave cell and control variables. When entered separately, student

Table 2. *Patience, Risk-taking, and Student Achievement: Migrant Analysis.*

	Full sample							Language spoken at home	
					Controls for test-taking effort			Residence	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Patience (country-of-origin)	0.779***		0.931***	1.032***	0.890***	1.021***	0.977***	0.718***	0.883***
	(0.115)		(0.116)	(0.133)	(0.114)	(0.100)	(0.105)	(0.117)	(0.151)
Risk-taking (country-of-origin)		0.183	−0.294**	−0.449***	−0.286**	−0.307**	−0.303**	−0.305**	−0.508***
		(0.210)	(0.122)	(0.140)	(0.119)	(0.120)	(0.114)	(0.115)	(0.165)
Positive reciprocity (country-of-origin)				−0.141					
				(0.157)					
Negative reciprocity (country-of-origin)				0.082					
				(0.087)					
Altruism (country-of-origin)				0.042					
				(0.144)					
Trust (country-of-origin)				−0.173					
				(0.138)					
Item non-response					−2.993***		−3.218***		
					(0.233)		(0.171)		
Item non-response (country-of-origin mean)							−3.319*		
							(1.691)		
Residence country by wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	80,398	80,398	80,398	80,398	80,398	36,668	36,668	48,556	24,520
Countries of origin	58	58	58	58	58	41	41	56	57
Residence countries	48	48	48	48	48	45	45	48	48
R^2	0.273	0.256	0.275	0.277	0.310	0.178	0.234	0.298	0.238
Difference between subsamples									
Patience (country-of-origin)								0.165 (0.130)	
Risk-taking (country-of-origin)								−0.203 (0.139)	

Notes: Dependent variable: PISA math test score, waves 2003–2018. Least squares regressions, including 180 fixed effects for each residence country by wave cell. Sample: students with both parents not born in the country where the student attends school. Item non-response refers to the share of questions not answered in the student background questionnaire following the achievement test. Control variables: student gender, age, dummy for OECD country of origin, imputation dummies. Robust standard errors adjusted for clustering at the country level in parentheses. Significance level: ***1%, **5%, *10%. Data sources: PISA international student achievement test, 2003–2018; Falk *et al.* (2018).

achievement is significantly positively related to patience in the students' home country (column 1) and insignificantly positively to risk-taking (column 2). In line with the previous cross-country findings, the coefficient on patience increases and the coefficient on risk-taking turns significantly negative when both are entered together (column 3), underscoring the interrelated and competing nature of the two cultural traits. Students from home countries with one SD higher patience perform 0.93 SD better on the PISA math assessment, and students from home countries with one SD higher risk-taking perform 0.29 SD worse.[7]

Column 4 additionally includes controls for the four other national GPS preference components of the country of origin. These cultural controls do not significantly affect student achievement and leave the significant effects of the two intertemporal preference components intact. In fact, the coefficient on risk-taking increases (in absolute terms) to −0.45 in this specification.

In sum, the migrant analysis confirms the strong and positive effect of patience on student skill development documented in the descriptive cross-country analysis, even with the same overall magnitude. Similarly, it replicates the negative effect of risk-taking once we account for patience, though the effect size is smaller.[8] The migrant analysis rules out that the cross-country results are due to omitted residence country variables. There is, of course, the possibility of remaining biases, some of which we address in the following robustness tests.

3.3. *Robustness Analysis*

To account for differences in students' test-taking effort, columns 5–7 of Table 2 control for individual and country-of-origin mean item non-response rates in the PISA student background questionnaires. Even though both enter significantly in explaining scores, the results on patience and risk-taking again hardly budge after controlling for these proxies for student effort.

Identification in the migrant analysis depends on the extent to which the national preferences of the country of origin provide a good proxy for the students' and families' actual preferences. A proxy for the extent to which families still hold their country of origin's influence is whether they still speak the language of their country of origin at home, rather than adopting the language of their new host country. The effects of the two home-country traits are 0.17 and 0.20 SD larger for those students who do not speak the residence country language at home compared to those who do (columns 8 and 9), although the differences are shy of statistical significance. These results are consistent with an interpretation that the treatment variables in the migrant analysis do in fact capture the impact of cultural values of the countries of origin.

Online Appendix D shows that qualitative results are very similar for OECD and non-OECD countries, for achievement in science and reading, for first- and second-generation migrants and migrants of different ages of migration, and for alternative migrant definitions. The Online Appendix also shows results for the alternative WVS and Hofstede preference measures.

Finally, we investigate whether several possible dimensions of selective migration pose a threat to identification in our migrant analysis. As a start, we note that neither economic conditions in the home country nor socio-economic differences in family background drive the estimates of national preferences (column 2 of Table 9 in the Online Appendix). Another way to address

[7] Results do not differ significantly between girls and boys (columns 3 and 4 of Table 8 in the Online Appendix).

[8] The differences in the point estimates on patience in the migrant analysis of Table 2 (columns 3 and 4) to the respective specifications in Table 1 are only marginally significant ($p < 0.1$) in the specification without the four other preference components and statistically insignificant ($p = 0.360$) in the specification with the other preference components. Both differences are statistically highly significant ($p < 0.001$) for risk-taking.

potential bias from fundamental background differences is to include fixed effects for the origin continent of the migrant students. Column 1 of Table 3 shows that effects get slightly stronger when variation across continents of origin is removed. This analysis also indicates that results are not driven by geographic clustering of preferences by continent or by (exogenous) outstanding performance of any specific group such as students from Asia, Europe or Latin America.

Migrants tend to be a selected subgroup from their countries of origin (e.g., Borjas, 1987; Grogger and Hanson, 2011). Note that migrant selectivity that is the same across the different origin countries that send migrants to a specific residence country does not bias the migrant results. But differential migrant selectivity that is correlated with average cultural traits of the sending countries could introduce bias. This type of selection bias should be more severe for countries of origin with higher variance in cultural traits. However, the standard deviations of the two preference measures within the country of origin do not enter the model significantly and do not affect the qualitative results (column 2).

Another way to gauge the relevance of differentially selective migration is to take into account the geographical and cultural distance between sending and receiving countries. A general pattern in the migration literature is that migrants from neighbouring countries may be less positively selected than migrants from more distant countries (see Hanushek, Ruhose, Woessmann, 2017, for US evidence), possibly because fewer hurdles have to be overcome. Controlling for the geographical distance between migrants' country of origin and residence country (using the distance measures from Mayer and Zignago, 2011) does not change our qualitative results (column 3). In column 5, we test whether effects vary with the cultural distance between the migrant students' country of origin and their residence country, as measured by the absolute difference in the preference measures between the two respective countries. The positive impact of patience does not vary with cultural distance, whereas the negative impact of risk-taking attenuates as cultural distance increases.

We also employ one direct measure of the differential selectivity of migrants based on their educational attainment. For each pair of sending and receiving countries, we compare the educational attainment of migrants in the residence country to the educational attainment of the populations of their respective countries of origin. We then measure migrant selectivity as the percentile of the country-of-origin distribution of educational attainment from which the average migrant in each residence country comes. Hanushek, Ruhose, Woessmann, (2017) produced this measure for immigrants into the United States, and we extend that analysis to the full matrix of origin and residence countries with available data. The measure of migrant selectivity is indeed positively associated with student achievement (column 7), but accounting for this differential selectivity does not affect our estimates of the impact of patience and risk-taking.

4. Channels of Impact

Our analysis has established robust relationships between the two preference components and student achievement without direct reference to underlying mechanisms. In the context of the canonical human capital production function, national preferences may influence student achievement through proximate inputs at the family, school, and institutional level as well as the productivity with which inputs are transformed into outcomes (see Online Appendix A.2).[9]

[9] Online Appendix E shows descriptive analysis that includes the proximate inputs as controls in our main analysis. Results indicate that a substantial part of the overall effects of the two preference components may work through the channels of these proximate inputs.

Table 3. *Addressing Selectivity of Migrants in the Migrant Analysis.*

	Continent-of-origin fixed effects	Cultural variance	Migration distance: Geographical	Migration distance: Cultural		Selectivity of migrant schooling	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Patience (country-of-origin)	0.976***	0.818***	0.925***	0.933***	0.870***	0.987***	1.048***
	(0.125)	(0.191)	(0.117)	(0.149)	(0.137)	(0.105)	(0.106)
Risk-taking (country-of-origin)	−0.331**	−0.284**	−0.302**	−0.539***	−0. 903***	−0.300***	−0.411***
	(0.127)	(0.141)	(0.121)	(0.143)	(0.179)	(0.109)	(0.093)
SD of patience (country-of-origin)		0.285					
		(0.307)					
SD of risk-taking (country-of-origin)		−0.241					
		(0.372)					
Geographical distance (in 1,000 km)			−0.010				
			(0.007)				
Patience (country-of-origin) × Patience distance					−0.287		
					(0.353)		
Risk-taking (country-of-origin) × Risk-taking distance					1.048***		
					(0.217)		
Selectivity of migrant schooling							1.269***
							(0.379)
Observations	80,398	80,398	80,398	29,019	29,019	39,725	39,725
Countries of origin	58	58	58	49	49	44	44
Residence countries	48	48	48	26	26	20	20
R^2	0.276	0.275	0.276	0.236	0.239	0.192	0.196

Notes: Dependent variable: PISA math test score, waves 2003–2018. Least squares regressions. Sample: students with both parents not born in the country where the student attends school. All specifications include residence country by wave fixed effects and control variables (student gender, age, dummy for OECD country of origin, imputation dummies). Column-specific additional control variables: column 1: fixed effects for continent of origin; column 2: SD of patience and risk-taking, respectively, in country of origin obtained from individual-level GPS data using individuals' sampling probability; column 3: geographical distance between respective residence and origin country according to most populous cities; column 5: interaction with difference in patience and risk-taking between respective residence and origin country (all variables demeaned); column 7: percentile of migrants' educational attainment on respective country-of-origin schooling distribution for each residence country. Robust standard errors adjusted for clustering at the country level in parentheses. Significance level: ***1%, **5%, *10%. Data sources: PISA international student achievement test, 2003–2018; Falk *et al.* (2018).

Table 4. *The Association of Patience and Risk-taking with Proximate Inputs in the Education Production Function.*

	Family inputs (1)	School inputs (2)	Institutional inputs (3)	Residual (4)
Upper bound				
Patience	0.800***	0.069***	0.060	0.289***
	(0.087)	(0.021)	(0.037)	(0.095)
Risk-taking	−0.500***	−0.017	−0.066	−0.690***
	(0.139)	(0.033)	(0.059)	(0.151)
Observations	49	49	49	49
R^2	0.646	0.200	0.061	0.335
Lower bound				
Patience	0.382***	0.044**	−0.012	
	(0.062)	(0.019)	(0.027)	
Risk-taking	−0.325***	0.003	−0.009	
	(0.099)	(0.030)	(0.043)	
Observations	49	49	49	
R^2	0.461	0.120	0.008	

Notes: Country-level least squares regressions. Dependent variables indicated in column headers. Upper/lower bound refers to whether the preference variables are included in the underlying estimation of coefficients for the combination of the three input vectors. See text for details. Robust standard errors in parentheses. Significance level: ***1%, **5%, *10%. Data sources: PISA international student achievement test, 2000–2018; Falk *et al.* (2018).

To investigate the potential channels through which the national preferences operate, we regress four country-level variables reflecting major categories of proximate inputs[10] on the two preference components, patience and risk-taking (upper panel of Table 4).[11] Patience is positively associated with all four input components, although the association with institutional inputs is not quite significant at the 10% level. The association and explained variance are strongest for family inputs (column 1) followed by the residual (column 4). The residual factor has the character of total factor productivity, combining any unmeasured input components with the effectiveness of input use. Similarly, risk-taking is negatively correlated with all four input components, although only significantly so for family inputs and the residual.

As the estimation underlying the input aggregation may be biased by omission of the deeper preference variables, the presented estimates serve as an upper bound. A similar aggregation estimation including controls for the two national preferences can serve as a lower bound. The lower bound procedure yields similar qualitative results of significant positive associations of patience with family and school inputs and a significant negative association of risk-taking with family inputs, only with expectedly smaller magnitudes (lower panel of Table 4). Interestingly, none of the other GPS preference measures (positive reciprocity, negative reciprocity, altruism, and trust) are significantly related to any of the input factors (not shown).

The observed patterns appear intuitive and highlight that the different proximate inputs—and particularly family inputs and residual productivity—may operate as channels through which the two intertemporal preferences affect student achievement. Of course, this analysis is inherently descriptive and should not be interpreted as a causal mediation analysis.

[10] Online Appendix F describes the construction of the four country-level input measures.

[11] Note that the analysis of channels is not meaningful for the migrant analysis. Migrants are not exposed to the school and institutional environment of the country that defines their cultural origin.

5. Conclusions

International differences in student achievement are at the forefront of many education policy debates, but the deeper reasons for why students in some countries perform better than in others are not well understood. While cultural differences have standardly been discussed as confounding factors in cross-country analyses of student achievement, we explicitly investigate specific cultural factors as deep determinants of student learning and skill investment. We focus on patience and risk-taking—the two preference components that reflect the intertemporal and risky nature of educational decisions—and combine international student achievement data from PISA with newly available data on national preferences from the Global Preference Survey.

In our cross-country analysis, patience is strongly positively and risk-taking negatively associated with student achievement. Importantly, ignoring the interrelatedness between the two positively correlated preference components leads to a substantial underestimation of both effects.

These results are confirmed in an identification strategy that compares migrant students from different country-of-origin cultures observed in the same residence country, eliminating any potential residence country confounders. In a final descriptive analysis, we show that national preferences likely influence educational achievement by affecting several proximate inputs of the education production function, in particular family inputs and residual productivity.

Taking an international perspective in studying the factors that influence student achievement comes with both advantages and challenges. The interest of this paper is understanding the relationship between national preferences and student achievement across countries, and the documented strength of the preference-achievement nexus indicates the first-order nature of this question. However, identifying causal effects in international data is particularly challenging because of the multitude of potential factors influencing student achievement. Our migrant analysis, together with a series of robustness analyses, are entirely consistent with the conclusions from the cross-country analysis. While addressing the most significant threats to identification of impacts of national preferences, other threats may remain. At the same time, it seems quite unlikely that any remaining bias would operate to eliminate the extraordinarily strong impacts of national preferences that we estimate.

While our results are important for understanding international achievement differences, they do not lend themselves to direct policy conclusions. Cultural traits of countries are slow moving and not easy to change (e.g., Guiso *et al.*, 2006; Bisin and Verdier, 2011). At the same time, the relevant preferences are clearly amenable to change both at the individual and national level (e.g., Bird, 2001; Alan and Ertac, 2018; Jung *et al.*, 2021). The insight that cultural traits matter for educational achievement should thus be accounted for when designing policy interventions, particularly those focused on family inputs.

Our results imply that any policy intervention needs to take into account the fundamental role that cultural traits play in setting the context and in facilitating achievement. National policies cannot simply copy another country's experience. Failure to consider context may also explain why many previous attempts at international improvement have been unsuccessful. Finally, the finding that national preferences have limited association with institutional factors suggests that improving the institutional structures of school systems—whose importance has been highlighted by prior analyses (Hanushek and Woessmann, 2011; Woessmann, 2016b)—is a viable policy mechanism for improvement that does not necessarily depend on cultural change.

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Additional Supporting Information may be found in the online version of this article:

Online Appendix
Replication Package

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