Review of Economic Studies (2021) **0**, 1–38 doi:10.1093/restud/rdaa002

Patience and Comparative Development

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First version received May 2018*; Accepted May* 2021 (*Eds.*)

This paper studies the relationship between patience and comparative development through a combination of reduced-form analyses and model estimations. Based on a globally representative dataset on time preference in 76 countries, we document two sets of stylized facts. First, patience is strongly correlated with per capita income and the accumulation of physical capital, human capital and productivity. These correlations hold across countries, subnational regions, and individuals. Second, the magnitude of the patience elasticity strongly increases in the level of aggregation. To provide an interpretive lens for these patterns, we analyze an OLG model in which savings and education decisions are endogenous to patience, aggregate production is characterized by capital-skill complementarities, and productivity implicitly depends on patience through a human capital externality. In our model estimations, general equilibrium effects alone account for a non-trivial share of the observed amplification effects, and an extension to human capital externalities can quantitatively match the empirical evidence.

Key words: Time Preference, Comparative Development, Factor Accumulation

JEL Codes: D03, D90, O10, O30, O40

The editor in charge of this paper was Nicola Gennaioli.

1. INTRODUCTION

A long stream of research in development accounting has documented that production factors and productivity play an important role in explaining international income differences (Hall and Jones, 1999; Caselli, 2005; Hsieh and Klenow, 2010). This line of work does not speak to the reasons why countries or subnational regions exhibit variation in these proximate determinants of comparative development in the first place. According to standard economic theory, the stocks of physical capital, human capital, or research intensity all ultimately arise from an investment process that crucially depends on the same structural parameter of time preference (e.g., Becker, 1962; Ben-Porath, 1967; Romer, 1990; Aghion and Howitt, 1992; Doepke and Zilibotti, 2014). Perhaps due to a previous lack of reliable and comparable data on time preference on a global scale, however, the relationship between patience and comparative development is not well-explored.

This paper utilizes a recently constructed globally representative dataset on patience to present a new set of stylized facts about the relationships between patience, accumulation processes and income at different levels of aggregation. To interpret these stylized facts, we analyze and quantitatively estimate an overlapping generations (OLG) model with cross-national and cross-individual heterogeneity in patience.

Our empirical analysis is based on the Global Preference Survey (GPS), a recently constructed global dataset on economic preferences from representative population samples in 76 countries (Falk et al., 2018). In this survey, patience was measured through a series of structured questions such as hypothetical choices between immediate and delayed monetary rewards. To ensure comparability of preference measures across countries, the survey items underwent an extensive ex ante experimental validation and selection procedure, and the cross-country elicitation followed a standardized protocol that was implemented through the professional infrastructure of the Gallup World Poll (Gallup Inc., 2012). Monetary stakes involved comparable values in terms of purchasing power across countries, and the survey items were culturally neutral and translated using state-of-the-art procedures. Thus, the data provide an ideal basis for the first systematic analysis of the relationship between patience and investment decisions at the micro level and macro level.

Using these data, we present a new set of stylized facts about the relationship between patience, the accumulation of production factors and income at various levels of aggregation. Across countries, average patience is strongly positively correlated with income and statistically explains about 40% of the between-country variation in (log) per capita income (Falk et al., 2018). This reduced-form relationship is shown to be robust across a wide range of empirical specifications, which incorporate controls for many of the deep determinants identified in the comparative development literature, such as geography, climate, the disease environment, anthropological factors, and social capital.

Because canonical macroeconomic models posit that heterogeneity in patience matters for income through its impact on accumulation decisions, we also investigate the correlations between patience and the proximate determinants of development. Here, we find that average patience is also strongly correlated with cross-country variation in capital stocks, savings rates, different measures of educational attainment, and total factor productivity (TFP).

While our analyses are correlational in nature, we investigate to what extent the link between patience and cross-country development is likely to be spurious. For instance, measured patience might not reflect actual time preference but instead be confounded by local inflation and interest rates or the quality of the institutional environment. Similarly, patience may be endogenous to education. While controlling for potentially noisy measures is no panacea for omitted variable bias, we gauge the role of these potential confounds for our analysis by controlling for inflation and interest rates, objective and subjective institutional quality, life expectancy, educational attainment, and standardized achievement test scores. We find that country-level patience remains strongly correlated with per capita income conditional on these covariates. We also show that the correlations between preferences and macroeconomic variables are specific to patience: none of the other measures from the GPS (such as risk aversion or altruism) are robustly related to income or accumulation.

Next, we leave the realm of cross-country regressions to study subnational and individual heterogeneity in patience, income and accumulation processes. First, akin to the approach taken by Gennaioli et al. (2013), we present estimations that link average regional patience to regional per capita income and educational attainment. While the corresponding regressions investigate the correlates of patience at an aggregate level, as called for by development theories, they also allow us to keep many factors such as the overall institutional environment constant by including country fixed effects. The results reveal robust evidence that, within countries, regions with more patient populations exhibit higher average educational attainment and higher per capita income.

Finally, we present conceptually analogous analyses across individuals, holding fixed the country or subnational region of residence. Here, again, patience is robustly correlated with higher household income, a greater propensity to save, and higher educational attainment. Taken together, our analyses show that patience is consistently correlated with income and factor accumulation across levels of aggregation. The within-country and within-region results arguably go a long way towards ruling out that variation in institutional quality, or survey interpretation are drivers of the correlation between patience and income.

A salient finding that emerges from the analysis at different levels of aggregation is a quantitatively large amplification effect: the elasticity of the dependent variables with respect to patience strongly increases in the level of aggregation. This is the case in two conceptually related ways. First, restricting attention to across-region (or across-individual) analyses, the patience coefficient in income regressions drops by a factor of 6 – 7 once country fixed effects are included. Second, comparing across-country, across-region and across-individual regressions, the patience coefficient suggests that a one-standard deviation increase in patience is associated with an increase in income per capita of 1.73 log points across countries, of 0.17 log points across regions within countries, and of 0.05 log points across individuals within countries.

Most likely, *some* fraction of the differences in coefficient estimates across levels of aggregation are driven by measurement error and resulting attenuation bias. After all, across-individual and across-region variation in patience is likely measured with more error than cross-country patience. At the same time, our data also strongly suggest that attenuation alone is very unlikely to generate the observed aggregation patterns. For example, the patience coefficient in individual-level regressions is much smaller in specifications with country fixed effects; this shows a smaller elasticity within country, which is consistent with an amplification effect but cannot be explained by greater measurement error since all individual-level regressions (with or without country fixed effects) rely on the same individual-level data. This suggests that the amplification effects reflect an economic mechanism rather than a statistical artifact.

To provide an interpretive lens for this collection of new stylized facts, we analyze a three-period general equilibrium OLG model in which heterogeneity in patience affects individual savings and education decisions. Aggregate production is characterized by capital-skill complementarities. As a result, the accumulation of physical capital and human capital (and, hence, factor incomes) feeds back into individual decisions through general equilibrium effects.

At the level of individual decision makers, the model delivers intuitive predictions, such as that individuals who exhibit higher patience have a higher propensity to become skilled, save more, and have higher lifetime incomes. Analogous qualitative predictions hold when comparing two economies that differ only in their average level of patience. However, as a consequence of general equilibrium effects, the quantitative magnitude of the elasticity of income with respect to average patience can be amplified relative to its individual-level analogue.

We then use the model to evaluate whether the systematic differences in coefficient estimates across levels of aggregation can plausibly be generated by the model. For this purpose, we consider two thought experiments: (i) marginally increasing individual-level patience, holding average patience, aggregate allocations and prices fixed; (ii) marginally increasing average patience, which leads to changes in aggregate allocations and prices. We quantify the model by calibrating standard parameters based on estimates from the literature. We then estimate the remaining structural parameters (for which no agreed-upon estimates exist) using an indirect inference approach. We implement these estimations by targeting as estimation moments the empirical patience elasticities that we observe in our regressions at different levels of aggregation.

In the baseline version of the model, total factor productivity is assumed to be fixed at the same level for both economies, so that patience can only matter for the accumulation of physical and human capital. Thus, potential amplification effects only arise as a result of price effects in general equilibrium. A helpful way to think about this model variant is that it corresponds to the empirical estimates across subnational regions, where human and physical capital may vary but the broader productivity environment (institutions, national policies etc.) is largely kept fixed.

Estimation of this baseline model delivers sensible parameter values. For example, we estimate average annual discount factors of $0.93-0.95$. When we simulate the baseline model using the estimated parameter values, the implied patience elasticity is about twice as large at the aggregate relative to the individual level. This shows that in the model general equilibrium effects alone can lead to substantial amplification. The magnitude of these simulated amplification effects resonates with the empirical amplification effects observed going from individual- to regional-level estimates. While this amplification effect is substantial, however, it is not large enough to entirely account for the empirically-observed amplification in cross-country regressions.

Thus, in a second step, we estimate model variants in which productivity is allowed to vary, and implicitly depends on patience through a human capital externality. We think of these specifications as mirroring our cross-country regressions, in which the broader productivity environment also varies. In these analyses, we find that the amplification of the elasticity of income and skill shares with respect to patience increases substantially, and comes close to matching the empirically-observed patterns. Through a series of sensitivity checks, we document that the magnitude of amplification effects is largely governed by (i) the magnitude of capital-skill complementarities and (ii) the size of human capital externalities. Taken together, the model offers an internally consistent way to think about the empirical results, tying together the correlations between patience and economic outcomes across levels of aggregation, while simultaneously shedding light on the substantial amplification effects. Moreover, the estimation results clarify that – in the context of our model – the empirically-observed variation in patience can rationalize the observed development differences and amplification effects.

This paper contributes to two lines of research in the literature on comparative development. The first, using development accounting, decomposes national income into production factors and productivity (the proximate determinants of development). The second involves research on the deep determinants of development and focuses on the roles of geography, climate, history, or social capital (e.g., Knack and Keefer, 1997; Olsson and Hibbs Jr., 2005; Spolaore and Wacziarg, 2009; Algan and Cahuc, 2010; Ashraf and Galor, 2013). Our paper relates to the development accounting literature in that it analyzes a potential mechanism related to a cultural factor that can generate variation in the proximate determinants of development (e.g., Doepke and Zilibotti, 2008, 2014). Instead of attributing differences in the accumulated factors to exogenous variation in productivity or institutions Hsieh and Klenow (2010), our results suggest that variation in patience can explain heterogeneity in income and in productivity, once one allows for externalities that work through accumulated factors. At the same time, because our paper is descriptive and takes patience as given, our work builds on contributions in the deep determinants literature that have pointed to the potential long-run origins of variation in patience (Chen, 2013; Galor and Özak, 2016). Our results also complement recent work that studies the intergenerational transmission and evolution of patience in response to economic incentives, and the overall economic environment, in a setting where patience determines human capital investment (Doepke and Zilibotti, 2018).

Our paper also contributes to a recent line of work that studies the effects of human capital accumulation on growth (Gennaioli et al., 2013; Squicciarini and Voigtländer, 2015). Several contributions have shown that more realistic representations of the human capital accumulation process account for a considerably higher fraction of income variation than previously thought (see, e.g., Erosa et al., 2010; Caselli and Ciccone, 2013; Manuelli and Seshadri, 2014). Our paper contributes to this literature by providing micro evidence for one hitherto unexplored mechanism (preference heterogeneity) that may generate variation in human capital. Our focus on preference heterogeneity also connects to recent papers on cross-country variation in hours worked (Jones and Klenow, 2016; Bick et al., 2018).

The remainder of the paper proceeds as follows. The data are described in Section 2. Section 3 presents empirical evidence for the reduced-form relationships between patience and development at the individual and aggregate level. Sections 4 and 5 present and estimate the model. Section 6 offers a concluding discussion.

2. DATA

Our analysis relies on the Global Preference Survey (GPS), a recently constructed data set on economic preferences from representative population samples in 76 countries.[1] In many countries around the world, the Gallup World Poll regularly surveys representative population samples about social and economic issues. The GPS contains a set of survey items that were explicitly designed to measure a respondent's time preferences, risk preferences, social preferences, and trust, that were part of the regular 2012 questionnaire of the Gallup World Poll (for details see Falk et al., 2018).

1. For data and documentation see `https://www.briq-institute.org/global-preferences/home`.

Four features make these data suited for the present study. First, the preference measures were elicited in a comparable way using a standardized protocol across countries. Second, the data cover representative population samples in each country, which allows for inference about between-country differences in preferences. The median sample size was $N = 1{,}000$ per country, for a total of 80,000 respondents worldwide. Respondents were selected through probability sampling and interviewed face-to-face or via telephone by professional interviewers. A third feature of the data is geographical representativeness in terms of the countries being covered. The sample of 76 countries is not restricted to Western industrialized nations, but covers all continents and various levels of development.

Fourth, the preference measures are based on experimentally validated survey items for eliciting preferences. To ensure the behavioral relevance of the measure of patience, the underlying survey items were designed, tested, and selected for the purpose of the GPS through a rigorous ex-ante experimental validation procedure (for details see Falk et al., 2021). In this validation step, subjects participated in choice experiments that measured preferences using real money. They also answered large batteries of survey questions designed to elicit preferences. We then selected those survey items that were (jointly) the best predictors of actual behavior in the experiments to form the survey module. In order to make these items cross-culturally applicable, (i) all items were translated back and forth by professionals; (ii) monetary values used in the survey were adjusted based on the median household income for each country; and (iii) pretests were conducted in 22 countries of various cultural heritage to ensure comparability. See Appendix A and Falk et al. (2018) for a description of the data set and the data collection procedure.

Patience is derived from the combination of responses to two survey measures, one with a quantitative and the other with a qualitative format. The quantitative survey measure consists of a series of five interdependent hypothetical binary choices between immediate and delayed financial rewards, a format commonly referred to as the "staircase" (or unfolding brackets) procedure. In each of the five questions, participants had to decide between receiving a payment today or a larger payment in twelve months:

> *Suppose you were given the choice between receiving a payment today or a payment in* 12 *months. We will now present to you five situations. The payment today is the same in each of these situations. The payment in* 12 *months is different in every situation. For each of these situations we would like to know which one you would choose. Please assume there is no inflation, i.e., future prices are the same as today's prices. Please consider the following: Would you rather receive amount x today or y in* 12 *months?*

The immediate payment x remained constant in all four subsequent questions, but the delayed payment y was increased or decreased depending on previous choices (see Appendix A for an exposition of the entire sequence of binary decisions). In essence, by adjusting the delayed payment according to previous choices, the questions "zoom in" on the respondent's point of indifference between the smaller immediate and the larger delayed payment, which makes efficient use of limited and costly survey time. The sequence of questions has 32 possible ordered outcomes that partition the real line from 100 Euros to 218 Euros into roughly evenly spaced intervals. In the international survey, the monetary amounts x and y were expressed in the respective local currency, scaled relative to the median monthly household income in the given country.

The qualitative measure of patience is given by the respondents' self-assessment of their their willingness to wait on an 11-point Likert scale:

> *We now ask for your willingness to act in a certain way. Please indicate your answer on a scale from* 0 *to* 10*, where* 0 *means you are "completely unwilling to do so" and a* 10 *means you are "very willing to do so". How willing are you to give up something that is beneficial for you today in order to benefit more from that in the future?*

Our patience measure is a linear combination of the quantitative and qualitative survey items, using the weights obtained from the experimental validation procedure.[2] As described in detail in Falk et al. (2021), the survey items are strongly and significantly correlated with preference measures obtained from standard incentivized intertemporal choice experiments. Moreover, the measures predict experimental behavior out of sample. The ex-ante validation of the survey items constitutes a methodological advance compared to the often ad-hoc selection of questions for surveys.

A clear advantage of the quantitative staircase measure relative to the qualitative one is that it closely resembles standard experimental procedures of eliciting time preferences and corresponds to how economists typically think about immediate versus delayed rewards. In addition, the measure is context neutral and precisely defined, making it less prone to culture-dependent interpretations. In recent work, Bauer et al. (2020) show that quantitative (staircase-type) survey questions reliably measure preferences also outside the Western world, while this is not necessarily the case for more qualitative questions like subjective self-assessments. Indeed, it turns out that the relationship between patience and comparative development that we identify below is almost entirely driven by the quantitative measure. Still, the analysis relies on the composite patience measure as it was developed in the experimental validation procedure.

The analysis is based on individual-level patience measures that are standardized, i.e., we compute z-scores at the individual level. We then calculate a country's patience by averaging responses using the sampling weights provided by Gallup (see Appendix A). In all figures and regressions, patience is scaled in the same manner, regardless of whether the level of aggregation is the individual, a subnational region, or a country. Figure 1 depicts the resulting distribution of patience across countries, relative to the world's average individual. Darker red colors and darker blue colors indicate less and more patience, respectively, where differences are measured in terms of standard deviations from the world's average individual, which is colored in white.[3]

All other data used in this paper stem from standard sources such as the World Bank's World Development Indicators or the Penn World Tables. Appendix A describes all variables and their sources.

2. Specifically, responses to both items were standardized at the individual level and then aggregated:

$$\text{Patience} = 0.7115185 \times \text{ Staircase measure } + 0.2884815 \times \text{ Qualitative measure },$$

with weights being based on OLS estimates of a regression of observed behavior in financially incentivized laboratory experiments on the two survey measures. See Falk et al. (2018, 2021) for details.

3. The variation in patience appears to reflect idiosyncratic variation that is not well-captured by other aspects of cultural variation. For example, the correlations between patience and trust and between patience and risk taking are only $\rho = 0.19$ and $\rho = 0.23$, respectively. Moreover, as shown below, the well-known correlation between trust and per capita income vanishes once patience is controlled for.

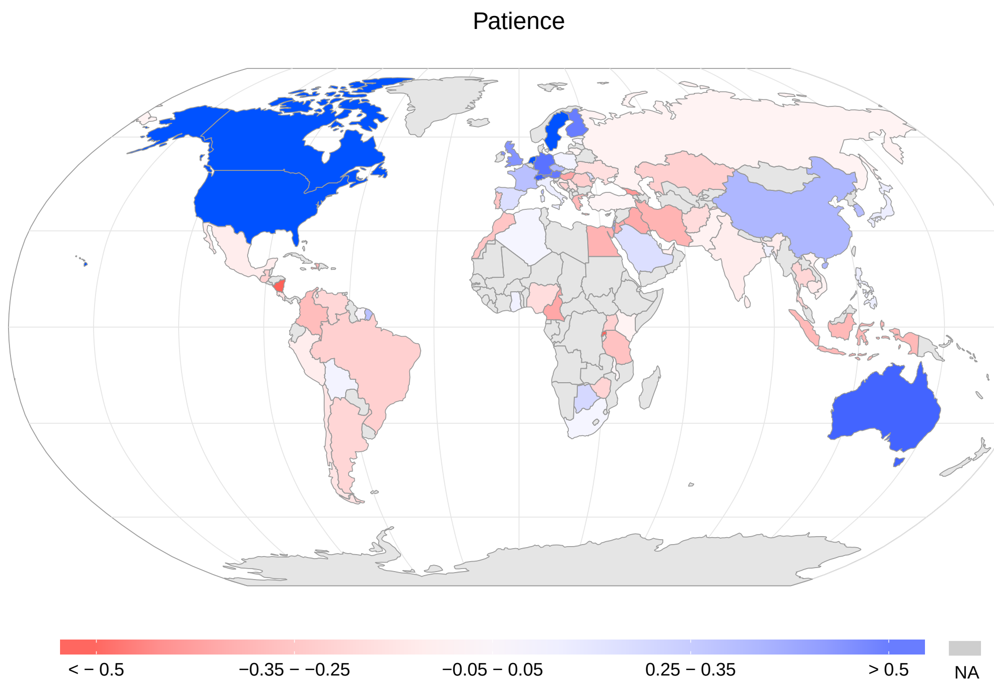

FIGURE 1
Distribution of patience across countries

Summary Statistics. Our individual-level data contain 80,377 respondents from 76 countries. Average age in our sample is 41.8 and 54% of all respondents are female. The individual-level patience index is correlated with demographics, as reported in Falk et al. (2018). Women are slightly less patient than men ($\rho = 0.04$), and respondents' subjective self-assessment of their math skills ($0-10$) is positively correlated with patience ($\rho = 0.13$). As discussed in Falk et al. (2018), there is a hump-shaped relationship between patience and age. In a joint regression, age, age squared, gender and subjective math skills explain about 2% of the global individual-level variation in measured patience.

3. PATIENCE AND DEVELOPMENT: EMPIRICAL EVIDENCE

A large body of theoretical work links heterogeneity in patience to the accumulation of production factors, and, hence, income. Motivated by this body of theoretical work, this section presents descriptive evidence on the relationship between patience, the accumulation of productive resources and income at three different levels of aggregation: across countries, across subnational regions, and across individuals.

3.1. *Cross-Country Evidence*

3.1.1. Patience and Income. Table 1 presents the results of a set of OLS regressions of per capita income on patience. Column (1) documents that a one standard deviation increase in patience is associated with an increase in per capita income of 2.32 log points. The raw correlation between the log of GDP per capita and the patience measure is 0.63, and patience alone statistically accounts for about 39% of the variation in log income per capita; also see Falk et al. (2018).[4] Columns (2) through (4) successively add a comprehensive set of geographic and climatic covariates, including controls for world regions, absolute latitude, longitude, the fraction of arable land, land suitability for agriculture, average precipitation and temperature as well as the fractions of the population that live in the (sub-) tropics or in areas where there exists the risk of contracting malaria.[5] Finally, column (5) additionally controls for genetic diversity and its square, and trust. While the inclusion of this large vector of covariates reduces the coefficient of patience by about 25%, it remains statistically significant and quantitatively large. Interestingly, the evidence indicates that trust, which has previously been identified as a driver of development (Knack and Keefer, 1997; Guiso et al., 2009; Algan and Cahuc, 2010; Tabellini, 2010), has little explanatory power once patience is included in the analysis. Figure 2 illustrates the conditional relationship for the estimates in column (5).

Robustness Checks. We conducted two sets of robustness checks. First, the results are robust to additionally controlling for average risk aversion, other geographical variables, linguistic, religious, and ethnic fractionalization, legal origin dummies, major religion shares, the fraction of European descent, and the genetic distance to the US.[6] Second, the relationship between patience and per capita income robustly appears in various sub-samples, e.g., within each world region, within OECD or non-OECD countries, or within former colonies and countries that have never been colonized.[7]

Growth Extension. Appendix D also presents an extension of the results on cross-national income differences by considering the link between patience and growth rates since World War II. To this end, we compute the (geometric) average annual growth rate in per capita GDP from different base years until 2015. We find that patience is robustly correlated with medium-run growth rates, both in univariate regressions and when we control for per capita income in the base year and additional covariates.[8]

3.1.2. Patience and Accumulation Processes. In standard textbook models, a reduced-form relationship between patience and development operates through accumulation processes. We therefore investigate whether patience is related to the levels of production factors and productivity as well as the corresponding accumulation flows.

4. The coefficient estimate in column (1) differs slightly from the one reported in Falk et al. (2018) because the regressions utilize different GDP data.

5. Following the World Bank terminology, world regions are defined as North America, Central and South America, Europe and Central Asia, East Asia and Pacific, South Asia, Middle East and North Africa, and South Africa.

6. See Table D.1 in Appendix D.

7. See Table D.2.

8. See Table D.3.

TABLE 1
Patience and national income

	Dependent variable: Log [GDP p/c]				
	(1)	(2)	(3)	(4)	(5)
Patience	2.32***	1.84***	1.60***	1.56***	1.73***
	(0.23)	(0.24)	(0.30)	(0.30)	(0.28)
Distance to equator			0.011	-0.0030	-0.033*
			(0.01)	(0.02)	(0.02)
Longitude			0.0023	0.0055	0.0077
			(0.01)	(0.01)	(0.01)
Percentage of arable land			-0.021*	-0.011	-0.0078
			(0.01)	(0.01)	(0.01)
Land suitability for agriculture			0.38	-0.10	0.15
			(0.66)	(0.48)	(0.44)
Average precipitation				0.0060	0.0019
				(0.00)	(0.00)
Average temperature				0.041*	0.013
				(0.02)	(0.02)
% living in (sub-)tropical zones				-1.29*	-1.18**
				(0.65)	(0.57)
% at risk of malaria				-1.45***	-1.46***
				(0.44)	(0.41)
Predicted genetic diversity					513.2***
					(130.93)
Predicted genetic diversity sqr.					-365.1***
					(96.08)
Trust					-0.076
					(0.42)
Continent FE	No	Yes	Yes	Yes	Yes
Observations	76	76	75	75	74
R^2	0.39	0.69	0.72	0.81	0.84

OLS estimates, robust standard errors in parentheses. * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$)

Physical Capital. To understand the relationship between patience and physical capital, we regress the stock of physical capital as well as three separate savings variables on patience. For each dependent variable, Table 2 presents OLS estimates of the unconditional relationship and of the relationship conditional on the full set of covariates from column (5) in Table 1.

Columns (1) and (2) document that patience is strongly correlated with the stock of physical capital, also conditional on controls. Columns (3) to (8) of Table 2 present the corresponding results for gross national savings rates, net adjusted national savings rates, and household savings rates as dependent variables. Gross savings rates are given by gross national income net of consumption, plus net transfers, as a share of gross national income. Net adjusted savings rates correspond to gross savings net of depreciation, adding education expenditures and deducting estimates for the depletion of energy, minerals and forests, as well as damages from carbon dioxide emissions. Household savings rates are measured as household savings relative to household disposable income. The data on household savings rates are based on surveys and are only available for OECD countries. Throughout, the results reveal a significant positive relationship between patience and savings. The finding that variation in patience is related to cross-country variation in household savings rates even within OECD countries is noteworthy, given the similarity of this subset of countries in terms of economic development and other characteristics.

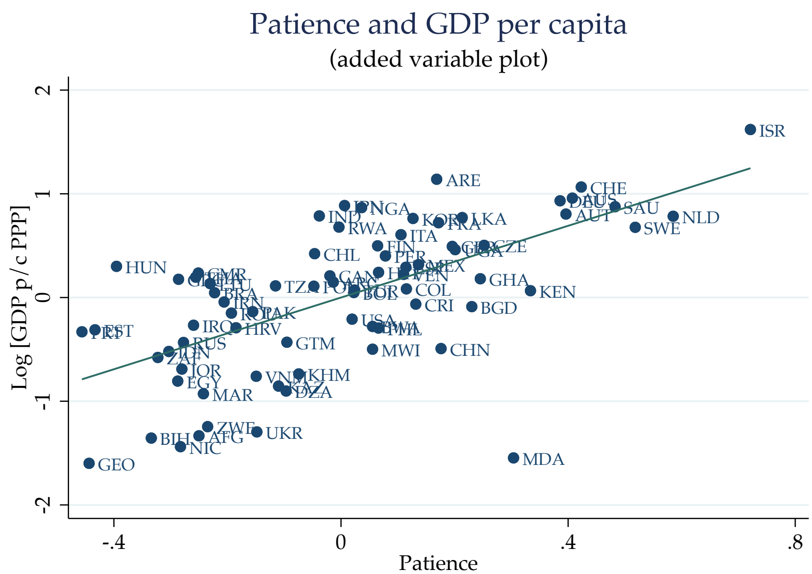

FIGURE 2

Patience and national income (added variable plot conditional on the full set of covariates in column (5) of Table 1).

TABLE 2

Patience, physical capital, and savings

	Dependent variable:							
	Log [Capital stock p/c]		Gross savings (% of GNI)		Net adj. savings (% of GNI)		HH savings (% of disposable inc.)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patience	1.94***	1.17***	7.43***	8.91***	6.08**	7.16*	8.52***	9.80***
	(0.27)	(0.29)	(2.41)	(3.27)	(2.34)	(3.62)	(2.72)	(3.31)
Continent FE	No	Yes	No	Yes	No	Yes	No	Yes
Additional controls	No	Yes	No	Yes	No	Yes	No	No
Observations	71	69	75	73	73	71	26	26
R^2	0.32	0.83	0.07	0.36	0.04	0.38	0.15	0.32

OLS estimates, robust standard errors in parentheses. Due to the small number of observations, in column (8), the controls are restricted to continent dummies. See column (5) of Table 1 for a complete list of the additional controls. * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$)

Human Capital. As baseline measures of human capital, we consider conventional quantitative measures of schooling. Our dependent variables are (i) the fraction of the population aged over 25 that has at least secondary education (Barro and Lee, 2013) and (ii) average years of schooling. Columns (1) – (4) of Table 3 report the results. The patience variable is robustly correlated with human capital, and statistically explains between 30% and 34% of the variation in the these variables.[9]

9. Comparable results are obtained with alternative measures of human capital, such as the fraction of the population aged over 25 that has obtained tertiary education, or a measure of the quality of

TABLE 3
Patience, human capital and productivity

	Human capital				Productivity			
	Dependent variable:							
	% Skilled		Yrs. of schooling		TFP		Log [# Researchers in R&D]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patience	38.5***	20.1***	4.34***	2.47***	0.29***	0.17**	2.70***	1.49***
	(5.45)	(7.20)	(0.58)	(0.86)	(0.05)	(0.07)	(0.35)	(0.50)
Continent FE	No	Yes	No	Yes	No	Yes	No	Yes
Additional controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	72	71	72	71	59	58	69	68
R^2	0.30	0.73	0.34	0.76	0.29	0.70	0.35	0.83

OLS estimates, robust standard errors in parentheses. The percentage skilled is the percentage of individuals aged 25+ that has at least secondary education (Barro and Lee, 2013). Number of researchers in R & D are per 1,000 population. Columns (5) – (6) exclude Zimbabwe because it is an extreme *upward* outlier in the TFP data from the Penn World Tables, which is likely due to measurement error. See column (5) of Table 1 for a complete list of the additional controls. * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$)

Productivity. Endogenous growth models highlight the role of patience for the accumulation of ideas and knowledge through research. Relatedly, factor productivity implicitly depends on patience in models that assume human capital externalities. Columns (5) – (8) in Table 3 document that patience is strongly correlated with both the TFP measure from the PWT and the number of researchers in research and development. For both dependent variables, the variance explained is again roughly 30%.

3.1.3. Assessing Endogeneity Concerns. While standard models such as the one presented in Section 4 below implicitly presume a causal role of patience for accumulation processes and income, a causal interpretation of our reduced form empirical results is subject to several potential criticisms: (i) the patience variable might not only measure patience but may reflect additional features of the external environment such as institutions, inflation, or interest rates; and (ii) the OLS correlations could be driven by omitted variables or reverse causality.

We do not claim that our analysis rules out all potential endogeneity concerns. Rather, we view this analysis as a first contribution that studies the systematic relationship between patience, accumulation and income, and that documents a novel set of stylized facts. Nonetheless, this section takes a more nuanced look at the data by investigating the extent to which the cross-country correlation between patience and per capita income is likely to be driven by omitted variables, measurement issues, or reverse causality.

Borrowing Constraints. Respondents might be more likely to opt for immediate payments in experimental choice situations if they expect higher incomes in the future and are borrowing constrained. To address this issue, we leverage the idea that borrowing constraints are likely to be less binding for relatively affluent people. We therefore employ the average patience of each country's top income quintile as an explanatory variable.

human capital as reflected by a measure of standardized math and science test scores (Hanushek and Woessmann, 2012), see Table D.4 in Appendix D.

As shown in column (1) of Table 4, the reduced-form relationship between patience and per capita income remains strong and significant using this patience measure.

Inflation and Interest Rates. If some respondents expect higher levels of inflation than others, or live in an environment with higher nominal interest rates, they might appear more impatient in their survey responses, even if they have the same time preference. Note, however, that the quantitative survey question explicitly asked people to imagine that there was zero inflation. Furthermore, we check robustness to this concern empirically by explicitly controlling for inflation (the GDP deflator) and deposit interest rates. We find that the reduced-form coefficient of patience remains quantitatively large and highly statistically significant after controlling for these factors; see column (2) of Table 4.

Subjective Uncertainty. In the quantitative decision tasks between payment today and in twelve months, respondents may face subjective uncertainty about whether they would actually receive the (hypothetical) payment in the future. Such subjective uncertainty is likely correlated with, or caused by, weak property rights or other institutions. Similarly, respondents may face high subjective uncertainty about receiving future payments if their remaining life expectancy is low. To provide a first pass at assessing the relevance of these considerations, we condition on both objective and subjective measures of the quality of the institutional environment as well as people's life expectancy. First, in column (3) of Table 4 we control for a property rights and a democracy index. Second, in column (4), we make use of the fact that Gallup's background data contain a series of questions that ask respondents to asses their confidence in various aspects of their institutional environment, including the national government, the legal system and courts, the honesty of elections, and the military. In column (5) we control for average life expectancy at birth. The results show that patience continues to be a strong correlate of national income, conditional on objective or subjective institutional quality, or life expectancy.

Cognitive Skills and Education. Our survey requires respondents to think through abstract choice problems, which might be unfamiliar and cognitively challenging for some participants. This could induce people to decide based on heuristics. Column (6) of Table 4 regresses GDP per capita jointly on patience and average years of schooling, and patience remains highly significant and large in magnitude. Similarly, column (7) shows that patience is significantly correlated with per capita income conditional on a measure of standardized math and science test scores (Hanushek and Woessmann, 2012). Finally, column (8) addresses the issue of decision heuristics. In particular, in the quantitative staircase procedure, respondents faced a series of five similar choices. Responses based on a simple heuristic such as "always money today / in the future" might lead us to overestimate the true variance in patience. We hence generate a binarized individual-level patience index that equals one if the respondent opted for the future payment in the first question and zero otherwise. Even though this measure is much coarser than our composite patience index, it is significantly correlated with per capita income.

Income Effects. It is also conceivable that the correlation between patience and national income is driven by reverse causality, i.e., that higher income causes people to be more patient (or to behave as if they are more patient in our survey tasks). One way of investigating the plausibility of such an account is to examine the relationship

TABLE 4
Patience and per capita income: Robustness

	Dependent variable: Log [GDP p/c PPP]							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patience of top income quintile	1.60***							
	(0.19)							
Patience		2.00***	0.77***	1.52***	1.04***	1.17***	1.37***	
		(0.33)	(0.27)	(0.41)	(0.24)	(0.24)	(0.27)	
GDP deflator		-0.068*						
		(0.03)						
Deposit interest rate		0.037						
		(0.04)						
Property rights			0.029***					
			(0.01)					
Democracy			-0.012					
			(0.05)					
Subj. institutional quality				0.014				
				(0.01)				
Avg. life expectancy					0.12***			
					(0.02)			
Avg. years of education						0.24***		
						(0.05)		
Math and science test scores							0.63**	
							(0.31)	
Patience (binarized staircase)								4.78***
								(0.68)
Continent FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76	59	72	59	76	72	49	76
R^2	0.69	0.64	0.79	0.69	0.81	0.77	0.72	0.66

OLS estimates, robust standard errors in parentheses. * $(p<0.10)$, ** $(p<0.05)$, *** $(p<0.01)$

between our patience measure and exogenous sources of income, such as oil rents. If it was true that higher income induces more patience in our procedures, then oil production (which is largely determined by natural resource endowments) should be correlated with patience. The left panel of Figure D.1 in Appendix D plots the raw correlation between log oil production per capita (measured in 2014 Dollars) and patience. The two variables are uncorrelated ($\rho=-0.04$), also conditional on the full set of controls in column (5) of Table 1 (see right panel of Figure D.1 in Appendix D). While these results do not necessarily rule out reverse causality from income and patience, they provide an initial piece of evidence that the patience variable picks up variation that is independent of income effects.

3.1.4. Other Preference Measures. The GPS includes information not only about patience but also on risk aversion, trust, altruism, positive reciprocity and negative reciprocity. Table 5 replicates the unconditional analyses from above by including all GPS measures. The results show that patience is always significantly correlated with the outcomes of interest, also conditional on other preferences and trust. Other measures are only inconsistently related with outcomes (see Falk et al. (2018) for a discussion of the correlation structure among the GPS measures).

TABLE 5
Other preference measures

	Dependent variable:						
	Log [GDP p/c]	Log [Cap. stock p/c]	Gross savings (% GNI)	% skilled	Years schooling	TFP	Log [researchers]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Patience	2.27***	1.80***	6.98**	37.2***	4.29***	0.24***	2.71***
	(0.27)	(0.26)	(3.26)	(6.28)	(0.68)	(0.06)	(0.30)
Risk taking	-0.90*	-0.95*	-2.79	-4.67	-0.82	0.050	-1.77***
	(0.45)	(0.49)	(4.76)	(9.75)	(0.94)	(0.08)	(0.65)
Trust	0.91*	0.98**	6.14	7.57	0.34	0.18*	0.39
	(0.49)	(0.46)	(4.82)	(9.97)	(1.02)	(0.10)	(0.59)
Altruism	-0.73	-1.05**	7.61*	-25.3**	-3.03***	-0.036	-0.94
	(0.51)	(0.44)	(4.02)	(10.09)	(1.10)	(0.09)	(0.62)
Pos. reciprocity	0.50	1.02**	-7.57*	24.7**	2.58**	-0.035	1.62**
	(0.51)	(0.51)	(4.39)	(11.74)	(1.15)	(0.12)	(0.65)
Neg. reciprocity	0.38	0.65	1.25	3.49	0.56	0.099	1.07**
	(0.48)	(0.42)	(3.54)	(9.96)	(1.05)	(0.09)	(0.51)
Observations	76	71	75	72	72	59	69
R^2	0.50	0.52	0.12	0.39	0.43	0.37	0.58

OLS estimates, robust standard errors in parentheses. * $(p<0.10)$, ** $(p<0.05)$, *** $(p<0.01)$

3.2. *Patience and Development Across Subnational Regions*

In a second step of the empirical analysis, we turn to regressions across subnational regions. This is possible since the individual-level patience data in the GPS contain regional identifiers (usually at the state or province level), which allows us to relate the average level of patience in a sub-national region to the level of regional GDP per capita and the average years of education from data constructed by Gennaioli et al. (2013). In total, we were able to match 704 regions from 55 countries.[10]

Our analysis is motivated by a long literature in cultural economics that suggests that psychological variables might vary considerably also within countries. While the regional level of analysis still pertains to an aggregate view on accumulation processes and income, the corresponding regression analyses have the important advantage of allowing us to account for unobserved heterogeneity at the country-level by including country fixed effects. In particular, accounting for country fixed effects relaxes potential concerns about the role of language and institutions for survey responses. Indeed, Gennaioli et al. (2013) provide evidence that while human capital varies considerably even within countries and is strongly correlated with regional income, within-country variation in institutional quality is uncorrelated with regional development.

The benefits of considering regional data naturally come at the cost of losing representativeness, since the sampling scheme was constructed to achieve representativeness at the country level. In some regions, we observe only a relatively small number of respondents. As a consequence, average regional time preference is estimated less precisely than country-level patience. This matters for our analysis because measurement error in regional patience will lead to attenuation bias that makes comparing country- and regional-level results difficult. We pursue two strategies to account for measurement error. First, we exclude all regions with fewer than 15 respondents from the analysis, which leaves us with 648 regions. Second, we apply techniques from the recent social mobility

10. See Appendix A for an overview of the number of regions per country.

TABLE 6
Regional patience, human capital, and income

	Dependent variable:					
	Log [Regional GDP p/c]			Avg. years of education		
	(1)	(2)	(3)	(4)	(5)	(6)
Patience	1.40***	0.19***	0.17***	3.64***	0.51***	0.47***
	(0.24)	(0.06)	(0.06)	(0.62)	(0.16)	(0.16)
Temperature			-0.025**			-0.055***
			(0.01)			(0.01)
Inverse distance to coast			0.41			0.88
			(0.25)			(0.58)
Log [Oil production p/c]			0.30***			0.044
			(0.07)			(0.06)
# Ethnic groups			-0.10*			-0.25*
			(0.06)			(0.13)
Log [Population density]			0.071**			0.19***
			(0.03)			(0.06)
Country FE	No	Yes	Yes	No	Yes	Yes
Observations	648	648	631	637	637	620
R^2	0.20	0.93	0.94	0.29	0.94	0.95

Regional-level OLS estimates, standard errors (clustered at the country level) in parentheses. Patience is shrunk patience, see equation (C.1) in Appendix C.2. * ($p<0.10$), ** ($p<0.05$), *** ($p<0.01$)

literature (Chetty and Hendren, 2018) and shrink regional patience to the sample mean by its signal-to-noise ratio.[11]

To provide some perspective on the variation in average regional patience, we discuss a few summary statistics. Recall that individual patience is standardized to have mean zero and standard deviation one. Average regional patience has a standard deviation of $\sigma=0.45$ (average country patience has standard deviation $\sigma=0.37$). Moreover, only 72% of the variation in regional patience is explained by country fixed effects. This suggests that our data exhibit sufficient within-country variation to meaningfully explore the link between regional patience and regional development.

Table 6 reports regression results for average per capita income and education as dependent variables. We estimate one specification without country fixed effects, one with country fixed effects, and one with additional regional-level covariates (Gennaioli et al., 2013). The results qualitatively mirror those established in the country-level analysis: we find significant relationships between patience and per capita income, and between patience and human capital, also conditional on country fixed effects.

Moving beyond the observation that patience is significantly correlated with income and education at the subnational level, a noteworthy observation is the change in the quantitative magnitude of the coefficient estimates. In particular, for both dependent variables, the patience coefficient drops by a factor of seven once country fixed effects are included (columns (2) and (5)). Moreover, the across-region coefficient estimates are substantially smaller than the corresponding across-country estimates reported in Table 1 and Table 3. We will return to this observation below when we discuss the role of aggregation effects.

11. For details see Appendix C.2.

3.3. *Individual-Level Evidence*

Finally, we study the relationship between patience, savings, education and income at the individual level using the GPS data. Table 7 presents the results of OLS regressions with three dependent variables: log household income per capita, a binary indicator for whether the respondent saved in the previous year, and a binary indicator for whether the respondent has at least secondary education. For each dependent variable, we report the results of four OLS specifications, one without any covariates, one with country fixed effects, one with regional fixed effects, and one with regional fixed effects and additional individual-level covariates.

The results document that patience is uniformly linked to higher income, a higher probability of saving, and a higher probability of becoming skilled.[12] This pattern holds conditional on a comprehensive vector of individual-level covariates including religion fixed effects, age, age squared, gender, cognitive skills, and three variables that are proxies for the subjectively perceived quality of the institutional environment (these variables are collected and constructed by Gallup, see Appendix B).

For a subset of 13 countries, our dataset contains information on whether the respondent owns a credit card, which we think of as a proxy for access to credit. Table D.6 in Appendix D additionally controls for this binary indicator, with very similar results as in Table 7.

Moving beyond the qualitative patterns, we again see that the coefficient estimate of patience drops by a factor of six in the income regressions once country fixed effects are included. This pattern is reminiscent of the results obtained in the regional-level analysis. We now turn to a first discussion of the mechanisms behind these aggregation effects.

3.4. *Potential Statistical Reasons for Amplification*

Throughout the empirical analysis, the patience variable is expressed as z-score at the individual level, and then aggregated up to the regional or country level. This implies that the point estimates in the income regressions can be directly compared across levels of aggregation. An inspection of the first column in each of the corresponding tables reveals a country-level patience coefficient of 2.32, a regional level coefficient of 1.40, and an individual-level coefficient of 0.34. A different way to look at this pattern is that – in both the regional- and individual-level regressions – the patience coefficient drops substantially (roughly by a factor of seven) once country fixed effects are included. This result is not due to the use of different specifications or data sources at different levels of aggregation. In fact, very similar aggregation effects emerge when we use the GPS data on patience and income and aggregate them up to the regional or country level.[13]

From an empirical perspective, the two obvious candidate explanations for the differences in the estimates across different levels of aggregation are measurement error and omitted variables at the aggregate level that correlate with average patience. In the following, we provide a brief discussion of both.

Measurement error constitutes a potential explanation for the large variation in coefficient estimates across levels of aggregation due to attenuation bias. In particular,

12. Comparable results are obtained with a more restrictive definition of being skilled, or for subjective measure related to the quality of human capital in terms of math skills (see Table D.5 in Appendix D) .

13. See Table D.7 in Appendix D.

TABLE 7. Individual patience, savings, human capital, and income

	Dependent variable:											
	Log [HH income p/c]				Saved last year				1 if at least secondary educ.			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Patience	0.34***	0.056***	0.049***	0.040***	0.051***	0.038***	0.038***	0.032***	0.061***	0.035***	0.033***	0.012***
	(0.05)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Age				0.58***				-0.059				0.20
				(0.20)				(0.32)				(0.24)
Age squared				-0.38				-0.056				-0.94***
				(0.23)				(0.30)				(0.22)
1 if female				-0.086***				-0.0057				-0.028***
				(0.02)				(0.01)				(0.01)
Subj. math skills				0.035***				0.017***				0.028***
				(0.00)				(0.00)				(0.00)
Subjective institutional quality				-0.042*				0.046				-0.062***
				(0.02)				(0.03)				(0.01)
Confidence in financial institutions				4.22***				5.15***				0.76
				(1.17)				(1.24)				(0.67)
Subjective law and order index				0.058**				0.012				0.00018
				(0.02)				(0.03)				(0.01)
Country FE	No	Yes	No	No	No	Yes	No	No	No	Yes	No	No
Subnational region FE	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Religion FE	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Observations	79245	79245	78271	46383	15260	15260	15260	10438	79357	79357	78403	46550
R^2	0.05	0.61	0.64	0.64	0.01	0.07	0.13	0.14	0.02	0.18	0.23	0.29

Individual-level OLS estimates, standard errors (clustered at the country level) in parentheses. The dependent variable in (1) – (4) is ln household income per capita; the dependent variable in (5) – (8) is a binary indicator for whether the individual saved in the previous year; and the dependent variable in (9) – (12) is 1 if the individual has at least secondary education. Age is divided by 100. All results in columns (5) – (12) are robust to estimating probit models. See Appendix B for a detailed description of all dependent variables. * $(p<0.10)$, ** $(p<0.05)$, *** $(p<0.01)$

the relationship between individual income and patience should be more attenuated than the country-level relationship if individual patience is measured with more noise than country-level patience. This is likely the case as measurement error washes out when aggregating patience at the country level. Similarly, it is almost certainly true that regional patience is measured with more error than country patience because of the smaller number of respondents. Thus, part of the difference in patience coefficients between country-, regions- and individual-level analysis is likely to be due to measurement error.

At the same time, two pieces of evidence strongly indicate that measurement error alone is unlikely to generate the observed aggregation effects. First, an argument that is based on measurement error cannot explain why – within individual-level or region-level analyses – the coefficient drops by a factor of about seven once country fixed effects are included. After all, these regressions all rely on the same level of aggregation (either individual or region). Instead, it appears that moving from a cross-country to a purely subnational comparison per se reduces the magnitude of the patience coefficient.[14]

A second piece of evidence against a pure measurement error explanation is the required magnitude of noise. We conduct simulations that provide an estimate of the magnitude of measurement error that would be required to generate the observed variation in coefficient estimates across different levels of aggregation. Suppose that observed patience p_o is given by $p_o = p_t + \alpha \cdot \epsilon$, where p_t is the respondent's true patience, α a scaling parameter and $\epsilon \sim \mathcal{N}(0,1)$ a noise term (recall that observed patience is also normalized to have a mean of zero and a standard deviation of one). The simulations, described in Appendix E, show that $\alpha = 6$ is required to explain the observed variation in coefficients. To see that this is unreasonable, note that the test-retest correlation of preference parameters is estimated to be slightly below 0.6 (Beauchamp et al., 2017), yet $\alpha = 6$ would imply a test-retest correlation of only $\rho = 0.02$.[15] While there is reason to believe that the test-retest correlation in heterogeneous large-scale survey samples would be lower than with student subject pools, an implied test-retest correlation of 0.02 appears too low to be reasonable. We conclude from our analysis that some other deeper mechanism must be at play that generates the amplification of effects.[16]

The other candidate explanation for the differences in the estimates across different levels of aggregation is omitted variables in the form of correlated aggregate effects as the result of equilibrium interactions or other externalities. In particular, abstracting from measurement error, it is known that, in the presence of omitted variables that correlate

14. Our individual-level coefficient estimates are broadly in line with those obtained using other medium-scale micro datasets in the literature that focus on particular countries. While direct quantitative comparisons are complicated by the use of different patience measures and income variables, the few available benchmarks reveal encouraging similarities. In the nationally representative German sample of Dohmen et al. (2010), the corresponding coefficient of individual patience in a regression with log income per capita as outcome variable is 0.09. In a sample of U.S. respondents in the Health and Retirement Study (aged 70+), the same coefficient is 0.23 (Huffman et al., 2017), though the sample is clearly more special than ours.

15. To generate a test-retest correlation close to 0.6, α would have to be approximately 0.75. However, with $\alpha = 0.75$, the coefficient of patience obtained at the country level would be only about twice as large as the individual-level coefficient, again at odds with the data.

16. An additional measurement-related issue that could generate differences in coefficient estimates between individual and country-level regressions is expansion bias resulting from a left-censoring of the patience variable. Indeed, in our data, about 56% of respondents always opt for the immediate payment in the quantitative staircase procedure, so that we can only identify an upper bound for their patience. Appendix E.2 discusses this issue in detail.

with patience at the country level, the country-level estimates and the (within-country) individual-level estimates of the patience elasticity estimate different parameters, since the country-level estimate also contains the correlated group effects (which could reflect, e.g., equilibrium effects or externalities). To see this, suppose that the structural model underlying the data is the same for all individuals and consider a model for the relationship between an outcome variable, e.g., income, y, and patience p for individuals i in countries j, with latent country-specific effects κ_j and a homogeneous slope, $y_{ij} = a_0 + a_1 p_{ij} + \kappa_j + u_{ij}$. Following Mundlak (1978) and Pakes (1983), let the latent effect be a function of average patience, with $\mathbf{E}[\kappa_j | \bar{p}_{.j}] = \bar{p}'_{.j}\gamma$. Then $y_{ij} = p'_{ij} a_1 + \bar{p}'_{.j}\gamma + e_{ij}$, and taking country means gives $\bar{Y}_{.j} = \bar{P}'_{.j}(a_1 + \gamma)$. Thus, estimates at the country level also reflect equilibrium effects or other externalities in addition to the individual-level relationship. Considering the possibility that patience is measured with error implies an observationally similar difference in the individual and aggregate estimates and it is not possible to disentangle both mechanisms in general. However, the availability of an intermediate level of aggregation, as in our case sub-national regions, provides further insights as to whether the observed amplification effect is due to omitted variables at the aggregate level or due to measurement error (for details, see Pakes, 1983). A comparison of the estimates at the levels of individuals, regions, and countries reveals that correlated country-level effects, and to a lesser extent correlated region-effects, are likely candidates for explaining the amplification effect, in contrast to measurement error.[17]

In the next section, we consider an model that features heterogeneity in patience across individuals and across countries. This model illustrates a potential economic (rather than statistical) mechanism behind aggregation effects by rationalizing the existence of correlated group effects as consequence of general equilibrium mechanisms and externalities.

4. A CONCEPTUAL FRAMEWORK

4.1. *Setup*

We present a deliberately simple model that builds upon previous contributions on the role of patience for the accumulation of physical capital (Ramsey-Cass-Koopmans), human capital (Becker, 1962; Ben-Porath, 1967), and potential human capital externalities on productivity (Lucas, 1988).[18] Consider an economy of overlapping generations of individuals that live for three periods. Each generation has unit mass and each period lasts for one unit of time. Individuals derive utility from consumption and are heterogeneous with respect to their patience. When young, all individuals work as unskilled workers in production and decide whether to become educated, which is analogous to becoming a skilled worker in the second period. Becoming skilled requires

17. Suppose that the correlated group effects and measurement error are mutually uncorrelated, then it can be shown that the difference between country-level estimates and estimates between regions within countries (region-level estimates conditional on country fixed effects) identifies the correlated effect of variation in country-level patience (for details, see Pakes, 1983). For instance, considering the results in Table D.7 in Appendix D, the estimate for this effect corresponds to $2.14 - 0.15 = 1.99$. This is similar to the effect obtained under the assumption of no measurement error, which corresponds to the differences between country-level estimates and estimates between individuals within countries (individual-level estimates conditional on country fixed effects) of $2.14 - 0.056 = 2.084$.

18. See also Acemoglu (2008) for a comprehensive overview of the role of time preferences for growth and Doepke and Zilibotti (2014) for the role of patience in an education-based growth model.

young individuals to spend a fraction $(1-\psi)$ of their time on the acquisition of human capital. During the second period of life, individuals work either as unskilled or skilled workers, depending on their previous education choice, and make savings decisions. During the third period of life, individuals retire from the labor market and finance consumption from their savings. At the aggregate level, saved income is transformed one-to-one into physical capital that can be used for production during the following period. The capital accumulated by one generation during their second period of life fully depreciates at the end of the third period of life.

Let generations be indexed by the period during which they are young. The preferences of individual i are represented by

$$U(i) = \ln c_t + \beta(i) \ln c_{t+1} + [\beta(i)]^2 \ln c_{t+2}\,, \tag{4.1}$$

where $\beta(i) \in (0,1)$ is the discount factor of individual i, which corresponds to this individual's level of patience. For analytical convenience, $\beta(i)$ is modeled as a draw from a uniform distribution $\beta \sim U[\chi-\varepsilon; \chi+\varepsilon]$, where $\chi > 0$ reflects the average level of patience in the population and where the density is $\frac{1}{2\varepsilon}$ (with $\varepsilon > 0$, $\chi > 0$ and $0 < \chi - \varepsilon < \chi + \varepsilon < 1$). In the analysis below, variation in $\beta(i)$ conditional on χ captures individual-level heterogeneity within an economy, whereas variation in χ reflects comparisons across model economies.

4.2. *Optimal Individual Accumulation Decisions*

Human Capital Acquisition. Becoming a skilled worker requires devoting a fraction $(1-\psi)$ of the first period of life to skill acquisition. We assume that the stock of human capital increases with the time spent on education according to a standard Mincerian specification, with the stock of individual human capital corresponding to $h = e^{\rho(1-\psi)}$, where $\rho > 0$ is the parameter for the return. For analytical simplicity, we restrict attention to a binary education choice.

Budget Constraints. Denote the wage of unskilled workers by w^L, the earnings of a skilled worker as $w^H h$, the savings rates of unskilled and skilled workers as s^L and s^H, and the return on capital as R. We assume that individuals cannot save or borrow when young.[19] The respective budget constraints are then

$$\text{unskilled:}\quad c_t^y = w_t^L\,, \qquad c_{t+1}^m = w_{t+1}^L \cdot (1 - s_{t+1}^L)\,, \qquad c_{t+2}^o = w_{t+1}^L \cdot s_{t+1}^L \cdot R_{t+2}\,, \tag{4.2}$$

$$\text{skilled:}\quad c_t^y = w_t^L \psi\,, \quad c_{t+1}^m = w_{t+1}^H h \cdot (1 - s_{t+1}^H)\,, \quad c_{t+2}^o = w_{t+1}^H h \cdot s_{t+1}^H \cdot R_{t+2}\,. \tag{4.3}$$

Individuals take wages and capital returns as given.

Optimal Individual Decisions. The optimal savings decision in the second period of life for an unskilled worker i of generation t is determined by maximizing (4.1) subject to (4.2). Analogously, the optimal savings decision for individual i conditional on becoming a skilled worker is determined by maximizing (4.1) subject to (4.3). Solving the individual

19. This assumption ensures a role of patience for education choices by preventing consumption smoothing through savings, see, e.g., Doepke and Zilibotti (2014) for a similar setup.

decision problems delivers the optimal savings rate as

$$s^L_{t+1} = s^H_{t+1} = \frac{\beta(i)}{1+\beta(i)}\,, \tag{4.4}$$

which is strictly increasing in individual i's patience $\beta(i)$. Due to log utility, the savings rate does not depend on the return to capital nor on the education status of the individual.

The choice to become a skilled worker involves a comparison of (indirect) lifetime utilities. The condition for becoming skilled is determined by whether the return for becoming skilled, which is given by the wage ratio $\eta_{t+1} = \frac{w^H_{t+1}}{w^L_{t+1}}$, matches the compensation that an individual requires for being willing to spend a fraction $(1-\psi)$ of the first period of life on acquiring human capital. After cancelling common terms (wages), substituting from the optimal savings decision and simplifying, the condition for a preference for becoming skilled is given by

$$\eta_{t+1} > \eta(i) = \frac{\psi^{\frac{-1}{\beta(i)(1+\beta(i))}}}{h}\,, \tag{4.5}$$

with $\eta(i)$ denoting the minimum compensation that is required for making the individual with patience $\beta(i)$ indifferent between becoming skilled or remaining unskilled. This minimum compensation is decreasing in patience $\beta(i)$ since a higher $\beta(i)$ implies a greater utility weight on the earnings premium that is associated with becoming skilled, thus implying a lower requirement for market compensation. Intuitively, the earnings premium from becoming skilled accrues during the second period of life and, through savings, also benefits the individual during the third period of life. Hence, the market premium that compensates an individual for the opportunity cost of time foregone for education in the first period of life is smaller the more patient the individual. For a given wage ratio $\eta_{t+1} = \frac{w^H_{t+1}}{w^L_{t+1}}$, condition (4.5) therefore implicitly determines a threshold level for patience, $\tilde{\beta}_t$, that determines the population share of skilled individuals.[20]

The model has straightforward predictions about how savings, education, and income respond to variation in patience at the individual level. Taking the aggregate allocation as given, a higher level of patience $\beta(i)$ is associated with a higher individual propensity to save as consequence of (4.4). Likewise, more patient individuals have a higher propensity to become skilled due to (4.5). As a result of these two mechanisms, lifetime income also increases in individual patience.

4.3. *Aggregate Equilibrium*

Production. The production of final output Y during period t combines the available stocks of physical capital, skilled labor and unskilled labor. In light of the empirical

20. The simple representation of the individual education decision as a binary choice problem illustrates the main mechanism while keeping the model tractable. In order to account for other unobserved and idiosyncratic factors that might influence education choices in reality and thus the patience elasticity, the decision to become skilled as determined by (4.5) could be extended by incorporating idiosyncratic heterogeneity that is orthogonal to the mechanism related to patience. In the empirical implementation below this is done by including a symmetrically distributed additive noise term with mean zero. The main empirical predictions regarding the role of patience for individual decisions remain unaffected by this since the effects of idiosyncratic heterogeneity wash out on average.

evidence regarding capital-skill complementarities (Duffy et al., 2004), we assume that the production function takes the form

$$Y_t = A_t \left[\left(K_t^\theta + H_t^\theta \right)^{\frac{\sigma}{\theta}} + L_t^\sigma \right]^{\frac{1}{\sigma}}, \tag{4.6}$$

with the aggregate capital stock in period t denoted by K_t, the stock of unskilled labor denoted by L_t, the effective stock of skilled labor denoted by H_t, and A_t denoting total factor productivity (TFP).[21] Consistent with empirical estimates, we assume $\sigma > \theta > 0$. Markets for capital, unskilled workers and skilled workers are competitive and factors are paid their marginal products. Income can be used for consumption or capital accumulation; saved income is transformed one-to-one into physical capital. From the determination of competitive wages, it follows that during the second period of their lives, skilled workers supply their human capital and enjoy an earnings premium

$$\eta_{t+1} h = \frac{w_{t+1}^H h}{w_{t+1}^L} = e^{\rho(1-\psi)} \cdot \left[K_{t+1}^\theta + H_{t+1}^\theta \right]^{\frac{\sigma-\theta}{\theta}} \frac{L_{t+1}^{1-\sigma}}{H_{t+1}^{1-\theta}}.$$

Factor Market Clearing. In a given generation, only individuals with $\beta(i) > \tilde{\beta}_t$ optimally decide to become skilled. Since unskilled labor is supplied by workers of two adjacent generations (during the first period of life and those that remain unskilled during the second period of life), the stock of unskilled labor is given by

$$L_t = \frac{1}{2\varepsilon} \left[\int_{\chi-\varepsilon}^{\tilde{\beta}_{t-1}} 1 \, d\beta + \int_{\chi-\varepsilon}^{\tilde{\beta}_t} 1 \, d\beta + \int_{\tilde{\beta}_t}^{\chi+\varepsilon} \psi \, d\beta \right], \tag{4.7}$$

where $\tilde{\beta}_{t-1}$ and $\tilde{\beta}_t$ correspond to the patience thresholds that determine the stock of skilled workers of generations $t-1$ and t, respectively. The stock of skilled workers in a given period is given by

$$H_t = \frac{1}{2\varepsilon} \int_{\tilde{\beta}_{t-1}}^{\chi+\varepsilon} e^{\rho(1-\psi)} \, d\beta. \tag{4.8}$$

Since individual savings differ across education groups as consequence of different labor incomes, the information about the population composition allows for the determination of aggregate capital accumulation, with capital supply given by

$$K_{t+1} = \frac{1}{2\varepsilon} \left[\int_{\chi-\varepsilon}^{\tilde{\beta}_{t-1}} \frac{\beta(i)}{1+\beta(i)} (w_t^L \cdot 1) \, d\beta(i) + \int_{\tilde{\beta}_{t-1}}^{\chi+\varepsilon} \frac{\beta(i)}{1+\beta(i)} (w_t^H \cdot h) \, d\beta(i) \right]. \tag{4.9}$$

Extension: Human Capital Externalities. In its most basic form, the model does not feature an effect of patience on factor productivity. In a model extension, we consider a simplified human capital externality of the stock of skilled workers on effective total factor productivity (e.g., Lucas, 1988),

21. We abstract from the consideration of different types of capital in terms of equipment and structures, as in Krusell et al. (2000).

$$A_t = \bar{A} \cdot H_t^{\gamma}, \tag{4.10}$$

where $\bar{A}$ captures heterogeneity in productivity that is orthogonal to accumulated factors (in the sense of a Solow residual) and $\gamma \geq 0$.

Equilibrium. The remaining analysis focuses on the steady-state equilibrium. The equilibrium is characterized by a skill share λ and the aggregate allocations of skilled and unskilled labor and capital, as well as the corresponding competitive prices such that all individual decisions are consistent with the prices and the aggregate allocation.[22] The key condition for equilibrium is the consistency of the indifference condition for education (4.5) with the earnings premium that emerges from the relative supply of skilled labor, and the corresponding capital supply and demand.[23]

In steady state, wages and the share of skilled individuals are constant, such that $\eta_{t+1} = \eta$ and $\lambda_t = \lambda$. This follows from the one-to-one mapping between λ and $\tilde{\beta}$ and solving the condition for becoming unskilled vs. skilled (4.5) at the point of indifference, which determines the threshold level for patience as

$$\tilde{\beta} = \frac{1}{2}\left[-1 + \sqrt{1 - 4 \cdot \frac{\ln \psi}{\ln(\eta h)}}\right].$$

Under the assumption that $\beta(i)$ is distributed uniformly, this mapping is $\lambda = \frac{\chi + \varepsilon - \tilde{\beta}}{2\varepsilon} \Leftrightarrow \tilde{\beta} = \chi + \varepsilon - 2\varepsilon\lambda$.[24]

In terms of comparative statics, a key result for the subsequent analysis is that the equilibrium share of skilled individuals is unambiguously higher in a more patient population. In particular, comparing across equilibria, the following conditions hold regarding the effect of an increase in χ: $0 < \frac{d\tilde{\beta}}{d\chi} < 1$, and $\frac{d\lambda}{d\chi} = \frac{1}{2\varepsilon}\left(1 - \frac{d\tilde{\beta}}{d\chi}\right) > 0$.[25] These conditions also imply that the threshold in terms of individual patience for becoming skilled is higher in a country with a higher average level of patience.

5. BRINGING THE MODEL TO THE DATA

5.1. *Testable Implications*

Approach. We are interested in evaluating the effect of an increase in individual or average patience on education and income, in particular how this effect varies with the level of aggregation. To construct model analogues for the regression results, the model analyzes two thought experiments. At the individual level, the thought experiment is to determine the cross-sectional average elasticity of income and education with respect to a change in individual patience $\beta(i)$, holding the aggregate allocation (reflected

22. See Appendix F.1 for a formal definition of the equilibrium and the corresponding proof of existence and uniqueness.

23. The consideration of orthogonal idiosyncratic heterogeneity implies a negative second-order effect on aggregate savings but does not affect the existence and uniqueness of equilibrium and thus only has a minor quantitative effect on aggregation.

24. The average level of patience of unskilled workers is then given by $\underline{\beta} = \chi - \varepsilon\lambda$. Equivalently, the average patience of skilled workers is $\bar{\beta} = \chi + \varepsilon(1-\lambda)$.

25. See Appendix F.2 for the derivations.

by the share skilled, λ, and the associated threshold for patience, $\tilde{\beta}$) fixed. This thought experiment matches the results of individual-level regressions with country (or subnational region) fixed effects, where the fixed effects absorb the aggregate allocation and prices.

At the aggregate level, the thought experiment assesses the consequences of a shift in average patience, χ, on the steady-state equilibrium. Conceptually, this reflects the effect of an increase in patience across economies that are identical otherwise. This shift leads to general equilibrium effects that need to be taken into consideration and quantified since the factor allocation and prices change. This thought experiment corresponds to the cross-country or cross-regions regressions above.

To fix ideas and for expositional clarity, we consider a country in which patience is distributed uniformly with mean $\mu=\chi$ and standard deviation $sd=\frac{2\varepsilon}{\sqrt{12}}$. For comparisons across steady states we consider a shift in average patience that corresponds to one standard deviation, i.e., we compare the benchmark allocation of a baseline country (country 1) to that in a second country with $\chi_2=\chi_1+sd>\chi_1$, all else equal. Note how this thought experiment corresponds to the empirical analyses above, in which the OLS coefficients are estimated using a patience variable that has standard deviation one.

Education. First, consider the effect of patience on an individual's decision to become skilled. It is clear from (4.5) that the propensity to become skilled can be expressed as a binary choice problem with the compensation that an individual requires for becoming skilled, $\eta(i)$, as latent variable. If the market compensation, η^*, is greater than this minimum compensation, the individual becomes skilled. In reality, other unobserved and idiosyncratic factors beyond patience influence the education choice. Therefore, we represent the empirical analogue of the decision to become skilled as a linear probability model in which the decision to become skilled is determined by (4.5) with an additive noise term u that is symmetrically distributed around zero, $\mathcal{I}_{\text{skilled}}(i)=\mathbb{1}\{\eta^*-\eta(\beta(i))+u(i)>0\}$.[26] Consequently, the marginal effect of an increase in patience on the propensity to become skilled is given by

$$\frac{\partial \mathcal{I}_{\text{skilled}}(i)}{\partial \beta(i)}=\frac{1}{2\varepsilon}\cdot\left|\frac{d\beta(i)}{d\eta(i)}\right|. \tag{5.11}$$

Notice that the effect of patience on the individual propensity to become skilled depends on the level of patience. The empirical estimate of the elasticity of individual education with respect to patience (Table 7) corresponds to the population average of a linearized version of this marginal effect. In our quantitative model analysis, we evaluate this expression at the threshold $\tilde{\beta}$.

At the aggregate level, the effect of a shift in the distribution of patience on the share of skilled individuals can be expressed as

$$\frac{d\lambda}{d\chi}=\frac{1}{2\varepsilon}\left(1-\frac{d\tilde{\beta}}{d\chi}\right)>0. \tag{5.12}$$

Since aggregate human capital is given by $H=e^{\rho(1-\psi)}\cdot\lambda$, this expression is also proportional to the (semi-)elasticity of aggregate human capital with respect to patience with $\frac{dH}{d\chi}=e^{\rho(1-\psi)}\cdot\frac{d\lambda}{d\chi}$.

26. See Appendix G for details.

We are interested in whether this aggregate elasticity is larger than the corresponding individual-level elasticity. A comparison of the size of the effects at the individual and at the aggregate level requires additional assumptions. First, since the individual effect increases with patience, the size of the effect depends on $\beta(i)$ at which the effect is evaluated. Since the patience threshold $\tilde{\beta}$ is higher in countries with a greater average patience (i.e., $\tilde{\beta}(\chi_2) > \tilde{\beta}(\chi_1)$), the individual effect is amplified in countries with greater average patience. In addition, as a consequence of the capital-skill complementarity, greater average patience induces general equilibrium effects that affect the aggregate skill share. This implies that the model is capable of generating an amplification of the elasticity of education with respect to variation in patience on the aggregate level compared to the individual level under certain conditions (see Appendix G for details).

Savings and Capital. In the model, savings are a continuous variable, while in our individual-level data we only observe a binary indicator for whether a respondent saved. For this reason, the quantitative analysis below will not use the elasticity of the individual savings rate with respect to patience as an empirical moment to be matched.

With the individual savings rate given as in (4.4), the average marginal effect of an increase in patience on individual savings is given by

$$\frac{\partial \bar{S}}{\partial \beta(i)} = \frac{1}{1+\tilde{\beta}} \left[\frac{(1-\lambda) \cdot w^L}{1+\chi-\varepsilon} + \frac{\lambda \cdot w^H h}{1+\chi+\varepsilon} \right], \tag{5.13}$$

where $\bar{S}$ denotes average individual savings.[27] This implies that the average effect of patience on individual savings is given by the corresponding weighted average effect on individual savings rates, with population shares and respective labor earnings as weights. These weights are fixed when considering the perspective of individual regressions, but they vary when comparing across steady states.

At the aggregate level, savings are given by the sum of total savings of unskilled and skilled workers whose per capita savings differ due to the difference in average patience across both groups, with skilled workers saving a higher share of their (higher) income. Thus, when estimating the elasticity of average savings (or capital) with respect to variation in patience across economies, the corresponding differences in the allocation in terms of the share skilled, λ, and wages also imply variation in the corresponding weights of the savings expression. Concretely, the effect of patience on aggregate capital is given by

$$\frac{dK}{d\chi} = \underbrace{\frac{\partial \bar{S}}{\partial \beta(i)} \frac{\partial \beta(i)}{\partial \chi}}_{\text{individual effect}} \underbrace{+ S^L \cdot \frac{dw^L}{d\chi} + S^H \cdot \frac{dw^H h}{d\chi} + \frac{\tilde{\beta}}{1+\tilde{\beta}} (w^H h - w^L) \cdot \frac{d\lambda}{d\chi}}_{\text{general equilibrium effects}},$$

where S^L and S^H denote the weighted savings rates among the groups of unskilled and skilled individuals, respectively. The first term captures the average increase in aggregate savings that results from higher individual savings rates in a country with a more patient population. The other terms capture the variation in aggregate savings due to general equilibrium effects that affect earnings.

27. See Appendix G for details.

For an amplification of the effect of patience on the aggregate level it is therefore necessary that the general equilibrium effect is positive. Notice that in a country with greater average patience the share of skilled is unambiguously larger. This implies that the wage of unskilled workers will be larger. With a sufficiently large capital-skill complementarity (as consequence of $\sigma > \theta > 0$), the decline in the wage of skilled workers and in the skill premium is small enough such that the general equilibrium effect is positive, giving rise to an amplification of the effect on the aggregate level.

Income. Finally, consider the effect of patience on income. Average individual income in the cross-section of individuals is given by the average of the per capita income of each of the three generations alive at this point in time. The marginal effect of variation in patience on individual income is then given by

$$\frac{\partial \bar{y}}{\partial \beta(i)} = \frac{\partial \bar{\mathcal{I}}_{\text{skilled}}}{\partial \beta(i)} \left[w^H h - (2-\psi) w^L \right] + R \cdot \frac{\partial \bar{S}}{\partial \beta(i)}, \tag{5.14}$$

where for simplicity bars over variables denote population averages. As before with savings, this corresponds to a weighted average of the effects of patience on the propensity to become educated and to save, with weights given by the aggregate allocation in terms of skill composition and the corresponding prices.

Turning to the effect of patience on aggregate income when considering cross-country variation, the resulting changes in the aggregate allocation imply variation in the corresponding weights of the income expression. Concretely,

$$\frac{dY}{d\chi} = \underbrace{\frac{d\lambda}{d\chi} \left[w^H h - (2-\psi) w^L \right] + R \cdot \frac{dK}{d\chi}}_{\text{direct effects}} + \underbrace{[2(1-\lambda)+\psi] \frac{dw^L}{d\chi} + \lambda \frac{dw^H h}{d\chi} + K \cdot \frac{dR}{d\chi}}_{\text{general equilibrium effects}}. \tag{5.15}$$

As before, the effect obtained from cross-country variation in patience is amplified compared to the effect from variation on the individual level if the general equilibrium effects are positive. Moreover, it becomes clear that even if the direct effects on education and savings are amplified at the aggregate level, this is not necessarily also the case for income if the general equilibrium effects are negative. Again, a sufficiently large capital-skill complementarity in production makes it more likely that the general equilibrium effects are positive.[28]

5.2. *Parameter Calibration and Estimation Approach*

We use a combination of model calibration and estimation to quantify the model. The baseline model contains eight parameters. The extension with a human capital externality involves an additional parameter. We calibrate parameters that are standard in macro-models using conventional estimates from the literature and estimate the remaining parameters as described below. In particular, we calibrate the CES elasticities σ and θ based on empirical estimates by Duffy et al. (2004).[29] We set the time requirement for becoming a skilled worker in terms of the fraction of the first period of life to $(1-\psi) = 0.2$,

28. See Appendix G for details.

29. Concretely, we use the average of their estimates for high skilled workers defined as workers with completed secondary education or college attainment.

TABLE 8
Calibrated parameters

Parameter	Value	Calibration Details
$1-\psi$	0.2	Fraction of young age required to become skilled (five additional years) (Caselli, 2017)
ρ	1.75^a	Corresponds to a (private) Mincerian return of 7% (Card, 2001; Psacharopoulos and Patrinos, 2018)
σ	0.62	CES (inverse): labor/capital compound (Duffy et al., 2004)
θ	0.38	CES (inverse): physical/human capital (Duffy et al., 2004)

Calibrated parameters. [a] With the Mincerian human capital production function, a return of $x=0.07$ for five years of schooling during a 25-year period of youth corresponds to $\rho=\frac{\ln(e^{0.07\cdot 5})}{0.2}=1.75$.

which is equivalent to five years with the length of a generation being 25 years. Finally, we assume a Mincerian return of 7%, which is in line with empirical estimates (e.g., Acemoglu and Angrist, 2000; Card, 2001; Belzil and Hansen, 2002; Psacharopoulos and Patrinos, 2018).[30] More precisely, given an average return of 7% over five additional years, this implies for the model $e^{0.07\cdot 5}=e^{\rho(1-\psi)}$. Inserting the calibrated value of ψ and solving for ρ yields $\rho=1.75$. Table 8 summarizes the calibration of these parameters.

The remaining parameters include the distributional parameters of the patience distribution, χ and ε, and the level of the Solow residual, $\bar{A}$. The extension of the model to a human capital externality invokes an additional parameter, γ. These parameters are either model-specific or no commonly agreed estimates exist that can be used for calibration. For instance, the literature has not settled on how large human capital externalities are in the data.[31] Consequently, we estimate these parameters using an indirect inference approach that allows us to estimate the remaining free model parameters by matching the patience elasticities of the variables of interest in the model to those obtained from the regressions in Section 3 above. In particular, the parameters are estimated by matching as empirical moments the patience elasticities of education at the individual level and aggregate level, as well as the patience elasticities of income at the individual level and aggregate level.[32]

To keep this analysis directly comparable to the reduced-form patterns, the simulated individual moments of the model correspond to shifts of individual patience by one standard deviation (as in the individual-level OLS regressions, in which patience was standardized into a z-score). Likewise, we consider a shift in average patience by one standard deviation, which again directly corresponds to the OLS point estimates at the country level. As a result, the remaining parameters to be estimated in the baseline estimation are given by the vector $\Theta=(\chi_1,\varepsilon,\bar{A})$, as χ_2 is implicitly determined by

$$\Delta\chi=\chi_2-\chi_1=sd=\frac{2\varepsilon}{\sqrt{12}}.$$

Unless noted otherwise, $\bar{A}$ is restricted to be the same across countries.

30. Regressing household income on years of schooling in our global individual-level data delivers an average Mincerian return of approximately 6.5%. However, this estimate has to be interpreted with caution because of the income measure and potential measurement error in the Gallup data.

31. See, e.g., Acemoglu and Angrist (2000); Moretti (2004); Ciccone and Peri (2006); Acemoglu and Autor (2012); Thönnessen and Gundlach (2013); Psacharopoulos and Patrinos (2018).

32. As noted above, we do not match the elasticities for savings due to the conceptual discrepancy that arises since the empirical data only contain binary information on whether a household saved or not.

TABLE 9
Matched elasticities and targets

Effect of patience	Model Moment	$\boxed{\tilde{Z}(\Theta)}$	Empirical Moment $[Z]$	Target Value
Individual level				
Income	$\frac{\partial \ln \bar{y}}{\partial \beta(i)}$	as in (5.14)	Table 7, col. (3)	0.05
Education	$\frac{\partial \mathcal{I}_{\text{skilled}}(i)}{\partial \beta(i)}$	as in (5.11)	Table 7, col. (11)	0.03
Country level				
Income	$\frac{Y_2 - Y_1}{Y_1}$	as in (5.15)	Table 1, col. (5)	1.73
Fraction skilled	$\lambda_2 - \lambda_1$	as in (5.12)	Table 3, col. (2)	0.20

The model moments for the elasticities at the country level are discretized versions of equations (5.15), and (5.12). For the fully parametric versions as implemented in the estimation, see (G.5), (G.1), (G.6), and (G.2) in Appendix G.

Estimation is based on a Wald-type minimization of the vector of quadratic differences of the standardized elasticities. Denote by Z the vector of elasticities obtained from reduced form regressions, and by $\tilde{Z}(\Theta)$ the corresponding vector of elasticities from the quantified model. The vector of parameter estimates $\hat{\Theta}$ is the solution to the minimization of the squared residuals

$$\hat{\Theta} = \underset{\Theta}{\arg\min} \quad \vartheta(\Theta)' \vartheta(\Theta), \tag{5.16}$$

where

$$\vartheta(\Theta) = \frac{\tilde{Z}(\Theta) - Z}{Z}$$

denotes the vector of residuals that corresponds to the relative mismatch between the model elasticities and the empirical targets. Table 9 provides an overview of the matched model quantities (elasticities) and corresponding empirical moments.

5.3. *Model Specifications*

To be able to shed light on the mechanisms behind the observed amplification effects in the data, we consider four variants of the model.[33]

Baseline. In the baseline version, we consider two model economies that only differ in their patience distribution, but without a human capital externality on TFP. Thus, patience only affects economic performance through the accumulation of physical capital and human capital. We think of this specification as conceptual analogue to the within-country-across-region regressions, reported in Section 3.2. Here, patience might affect the formation of physical and human capital, but the broader productivity environment is effectively held constant in these regressions. For example, national institutions, policies or the supply of educational resources plausibly affect the productivity environment, but are largely fixed when comparing subnational regions within the same country.

33. We discuss additional robustness checks below in Section 5.5.

HC Externality (estimated). To account for systematic differences in productivity across countries, which might also influence the accumulation of factors (Hsieh and Klenow, 2010), we then estimate an extended version of the model that accounts for the observed differences in TFP across countries. Specifically, we estimate the parameter that governs a potential human capital externality, γ while keeping $\bar{A}$ fixed across both economies. We think of this model variant as analogue of the cross-country regressions, where the broader productivity environment also varies, and where patience could implicitly affect the supply of national policies or other productivity shifters through the aggregate stock of human capital.

HC Externality (calibrated). As we will see below, allowing for a human capital externality increases the amplification effects between individual-level and country-level analyses substantially. This raises the natural question how sensitive our results are to the magnitude of the human capital externality. Given that no widely agreed-upon magnitude for this externality exists, we check sensitivity by calibrating $\gamma = \frac{\rho}{2}$. We view this calibration exercise as a conservative approach that complements an approach of directly estimating γ in light of the difficulties associated with disentangling social returns to human capital from private returns (see, e.g., Ciccone and Peri, 2006; Psacharopoulos and Patrinos, 2018) and recent evidence for aggregate returns to human capital exceeding returns in standard Mincerian regressions (Queiro, 2021).

Development Accounting: TFP variable, patience fixed. A natural concern with our empirical analyses is the presence of omitted variables. In particular, it is conceivable that patience is strongly correlated with income (especially across countries) because variables that are typically summarized as contributing to TFP might covary with patience, such as institutions or the quality of national policies. If this was the case, the amplification effects documented above would partly reflect omitted variable bias. To assess the plausibility of such an account, we estimate a model variant in which average patience χ is held fixed across the two economies under consideration. Instead, in this model variant we estimate two separate levels for $\bar{A}_1$ and $\bar{A}_2$, as is commonly done in the development accounting literature. That is, in these estimations, any differences in aggregate outcomes are exclusively driven by exogenous differences in TFP. We will then conduct the following thought experiment: Suppose that both economies are equally patient (fixed χ), yet the high-TFP one *appears* more patient in the GPS survey data. Then, can the observed amplification effects (and outcome differences between seemingly patient and impatient countries) be rationalized as a result of TFP differences? By addressing this thought experiment, the analysis will shed light on two aspects: whether exogenous variation in TFP alone is sufficient to rationalize the patterns in the data, and the potential value added of a patience-related amplification mechanism.

5.4. *Estimation Results*

Amplification Effects. Table 10 shows the results of the estimation of the different model specifications. Throughout the different specifications, the estimation delivers reasonable parameter values for patience. In particular, noticing that the estimates of χ correspond to the country-average of a 25-year discount factor, the estimates are equivalent to an average annual average discount factor of 0.93 to 0.95 (a discount rate of $5-7\%$).

TABLE 10
Estimated parameters

Model	Baseline	Extensions		Dev. Acc.
		HC-Externality (estimated)	HC-Externality (calibrated)	
χ_1, χ_2	0.16, [0.25][a]	0.16, [0.25][a]	0.12, [0.19][a]	0.16, [0.16][c]
ϵ	0.16	0.16	0.12	0.16[c]
$\frac{\bar{A}_1}{\bar{A}_2}$	1	1	1	2.55
γ	0	1.98	0.88[b]	0[c]

Parameters in brackets [ ] are derived from estimated parameters. [a] Level of χ_2 as implied by the estimated values of χ_1 and ε. [b] Calibrated to $0.88 = \frac{\rho}{2}$. [c] Values fixed as in baseline model.

Table 11 reproduces the reduced-form estimates of the elasticities of the various variables of interest with respect to patience in our data, and compares them with estimated model quantities. We begin by estimating the baseline version of the model without a human capital externality ($\gamma = 0$). This is the most restrictive version of the model in terms of explaining amplification effects. The results for this baseline specification – in which TFP is fixed across economies – are shown in column (2) of Table 11. The individual-level elasticities of income and education with respect to variation in patience obtained with the model closely resemble the empirical estimates, as shown in the upper panel. The bottom panel of the table shows the corresponding elasticities for variation in patience across economies. The baseline version of the model delivers a moderate amplification of the elasticity in income by a factor of about two. Interestingly, this magnitude of amplification corresponds to the patterns observed in the reduced-form regressions across subnational regions in column (3) of Table 6. The fact that the observed amplification is much larger at the country level – and that this cannot be reproduced by our baseline specification – suggests a potential role for TFP differences. Indeed, researchers have argued that many barriers to increasing educational quality are not primarily financial or technological but instead political in nature (Duflo, 2001; Acemoglu and Autor, 2012). Since these factors likely respond to national policies, there is reason to believe that regional levels of development may respond to national factors. To the extent that national policies respond to national patience, this would explain why the observed amplification is considerably smaller at the regional level.

To account for these national productivity factors in a parsimonious way, we then estimate the model variant in which γ (the externality) is a free parameter to be estimated. In Table 10, the estimation yields $\gamma = 1.98$, which is slightly larger than the value of the private return to human capital ($\rho = 1.75$) that is implied by a Mincerian return of 7%. Column (3) of Table 11 presents the results on amplification. In this version of the model, the individual-level patience elasticities are matched, and the model also delivers a large amplification of elasticities at the aggregate level that closely matches the data.

Given the strong increase in the observed amplification effect as a result of allowing for a human capital externality, we investigate the sensitivity of our results by calibrating $\gamma = \frac{\rho}{2}$. In column (4) of Table 11, we see that this version of the model again matches the empirical individual-level elasticities well. In addition, the elasticity of the fraction skilled with respect to patience is also matched closely. Regarding income, the observed amplification is now by a factor of 16. This is about half as much as with an estimated human capital externality, but nevertheless substantial in magnitude.

TABLE 11
Quantified model vs. data

	Effect of one SD increase of patience				Fixed χ
	Data (Baseline Controls)	Model			Model Dev. Acc.
		Baseline	Extensions		
			HC Externality (estimated)	HC Externality (calibrated)	
	(1)	(2)	(3)	(4)	(5)
			Individual level		
Income	0.05	0.05	0.05	0.05	0.05^a
Education	0.03	0.03	0.03	0.02	0.03^a
			Country level		
Income	1.73	0.11	1.74	0.80	1.79^b
Fraction skilled	0.20	0.16	0.18	0.16	0.02^b

The effect sizes in the simulated model are obtained after estimating the parameters through indirect inference as reported in Table 10. In the baseline, estimated parameters are χ_1, ε, and $\bar{A}$ by matching as moments the effects of patience on individual income, individual propensity to become skilled, aggregate income and aggregate skill share. For details on the target moments from the data see Table 9. ^{a} Effect of one standard deviation increase in individual patience β. ^{b} Effects of comparing across two countries with identical patience distributions, but with different levels of $\bar{A}$.

Finally, we present the results for the development accounting scenario in which average patience is fixed across economies, yet TFP levels are estimated for both countries. Column (5) of Table 11 presents the corresponding results. For the patience elasticity of income at the individual level, the patterns are similar to the other versions of the model. At the country level, we see that this version of the model does a very good job at matching the income difference between the high and low TFP countries (which we here interpret as "seemingly patient and impatient countries in the GPS"). At the same time, the difference in share skilled between the high and low TFP country are much smaller than the ones observed in the data, and also much smaller than the ones generated by our model variants that feature variable country-level patience χ.

Non-Targeted Moments. To further assess model performance and the plausibility of the estimated parameters, we also compared other, non-targeted data moments obtained from reduced form estimates or raw data to the corresponding moments obtained from the model estimation. These moments include elasticities of physical and human capital accumulation with respect to patience that have not been targeted in the estimation and thus allow for an assessment of the fit of the different specifications of the model. In addition, we consider other moments that are relevant from the perspective of comparative development. The results reveal that, by and large, the moments implied by the estimates of the different specifications of the model resemble the empirical moments, where the model extension with a human capital externality on TFP again provides the best overall fit; in comparison, the model variant with fixed patience but variable (exogenous) TFP fits the data rather poorly.[34]

34. See Table H.8 in Appendix H for details.

Sensitivity Analyses: Capital-Skill Complementarity. To assess the sensitivity of the results with respect to the magnitude of the capital-skill complementarity, we present a modification of our baseline model (without human capital externality) in which we do not calibrate the CES parameters σ and θ, but instead estimate them. The results of these estimations are similar to the baseline results.[35] If anything, this exercise delivers an even stronger capital-skill complementarity while improving the fit moderately. In a second sensitivity check, we estimate a model version in which the complementarity is calibrated to be considerably smaller than in our baseline specification ($\sigma = 0.51$ and $\theta = 0.49$). This reduces the observed income amplification relative to the baseline (from a factor 2.2 to 1.8 for income).

Sensitivity Analyses: Human Capital. Appendix H shows that our results are robust to allowing for both a human capital externality and TFP differences that are unrelated to human capital. The estimation of the individual return to education, ρ, delivers a slightly more pronounced amplification of the aggregate patience elasticities, but an otherwise fairly similar performance as the baseline model. Finally, we also estimated a version of the model that focuses on the role of upper-tail human capital. This version is motivated by arguments that the social returns to education are plausibly larger than is commonly estimated in cross-sectional data because the latter ignore the "level" effect that results from having highly skilled workers or entrepreneurs who run more productive firms and thereby increase the productivity of the entire workforce (Gennaioli et al., 2013; Queiro, 2021). When incorporating a reduced-form version of this perspective, the model delivers a similar amplification and performance. See Appendix H for details.

5.5. *Discussion*

Overall, the estimations yield three findings. First, even without variation in TFP, the model generates a non-trivial amplification effect in coefficient estimates going from the individual level to the aggregate level. This amplification is comparable to the amplification observed in the data when comparing individual-level and regional-level results.

Second, once variation in TFP is incorporated, the model predictions get closer to the coefficients obtained in cross-country analyses. This is consistent with productivity differences (such as national policies or supply of schooling) that are endogenous to average patience contributing to the observed amplification patterns.[36] For example, if patient populations opted for institutions designed to foster long-term growth as opposed to short-term rent extraction, these institutions may entail additional positive effects on factor accumulation and income.

Third, an alternative model in which the true underlying variation is not in patience but instead in TFP provides a less convincing model fit. In particular, in the model simulations, exogenous differences in TFP are unable to quantitatively match the observed variation in skill shares. In contrast, the assumed exogenous variation in patience induces large variation in both income and skill shares. These

35. See Tables H.9, H.10, and H.11 in Appendix H for details.

36. In this respect, the results relate to the literature on aggregation and aggregation bias that has focused on heterogeneity of tastes and non-linearities in shocks (Blundell and Stoker, 2005) and that has pointed to potential biases in coefficient estimates due to the neglect of variation in aggregate conditions (Hanushek et al., 1996).

results speak to the literature on development accounting. The conventional way to account for development differences is to investigate to which extent external factors that are reflected in TFP are required to account for income differences. As documented in the literature, the neo-classical growth model typically requires large TFP differences between countries to account for observed differences (see, e.g., Hall and Jones, 1999; Bils and Klenow, 2000; Caselli, 2005). Several recent papers have argued for TFP differences interfering with quality-adjusted human capital accumulation or early childhood investments in education, showing that this reduces the variation in unexplained TFP that is required to explain the income gap.[37] Our approach complements these contributions by highlighting the potential role of patience rather than education (which is an endogenous object) itself.

6. CONCLUDING REMARKS

In this paper, we have documented two sets of stylized facts. First, across levels of aggregation, differences in income as well as the accumulation of human capital, physical capital, and the stock of knowledge are systematically linked to variation in patience. Second, the data reveal strong aggregation effects with respect to patience. The analysis of a stylized general equilibrium model that allows for heterogeneity in patience within and across countries has shown that both patterns are consistent with economic theories of intertemporal choice. The results from a quantitative analysis of our model are consistent with the idea that the difference in magnitude of coefficients across levels of aggregation is partly driven by general equilibrium effects and human capital externalities.

We highlight three broad avenues for future research. First, our paper has only provided a first step towards understanding the relationship between patience and development, in particular given that our analyses are correlational in nature. Ultimately, we cannot (and do not intend to) rule out categorically that heterogeneity in patience reflects general circumstances such as institutional quality or education. At the same time, even if a variable such as institutional quality was the ultimate driver of the results in this paper, the mechanism would likely partly operate through patience. Still, an important question concerns the ultimate origins of variation in patience. Among the few candidate determinants that have been proposed are religion (Weber, 1930), cultural legacy as manifested in very old linguistic features (Chen, 2013), historical agricultural productivity and crop yield (Galor and Özak, 2016), mortality (Falk et al., 2019), as well as migratory movements of our very early ancestors (Becker et al., 2020). Future research might be able to disentangle the causal mechanisms that are at play here, perhaps along the lines of theoretical contributions that emphasize the two-way links between patience and education or income (Becker and Mulligan, 1997; Doepke and Zilibotti, 2008).

A second open question concerns the scope of the amplification mechanism at the regional level. Our main argument in the model estimation section was that aggregate productivity is largely held constant in across-region comparisons, so that – from the perspective of the model – potential amplification effects in cross-regional regressions

37. For instance, Hsieh and Klenow (2010) argue that TFP differences are amplified through their influence on the accumulation of factors. Erosa et al. (2010) and Manuelli and Seshadri (2014) find that differences in human capital substantially amplify TFP differences across countries. Schoellman (2012) makes a related point based on a novel methodology designed to measure differences in human capital quality.

reflect price effects. At the same time, the magnitude of cross-region differences in TFP and its link to patience is still an open question.

Third, while prior micro studies have focused on linking patience to human capital and physical capital accumulation, less is known about the effects that variation in patience might exert on productivity differences. This question seems particularly relevant from the perspective of our model estimations, in which the empirically-observed amplification patterns can only be explained in the presence of human capital externalities on productivity.

Acknowledgements. The authors thank the editor, Nicola Gennaioli, four referees, and Daron Acemoglu, Michael Burda, Klaus Desmet, Oded Galor, Nicola Gennaioli, Jeff Grogger, Luigi Guiso, Robert Hall, Ömer Özak, Matthias Sutter, Felipe Valencia, Nico Voigtländer, Joachim Voth, David Weil, David Yang, Fabrizio Zilibotti as well as seminar audiences at the 2015 NBER Political Economy Meeting, Columbia, Humboldt University Berlin, IFN Stockholm, Konstanz, Max-Planck Institute for Collective Goods Bonn, Stanford, and UCLA Anderson for valuable comments and discussions. Ammar Mahran provided outstanding research assistance.
Uwe Sunde acknowledges funding from the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) through CRC TRR 190 (project number 280092119, Project A07). Armin Falk and Thomas Dohmen acknowledge funding from the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) through CRC TR 224 (Project A01) and Germany's Excellence Strategy – EXC 2126/1 – –390838866.
A replication package is available on the Zenodo repository at `https://doi.org/10.5281/zenodo.5589052`.

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