Patience and Comparative Development*

Thomas Dohmen Benjamin Enke Armin Falk
David Huffman Uwe Sunde

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Abstract

This paper studies the role of heterogeneity in patience for comparative development. The empirical analysis is based on a simple OLG model in which patience drives the accumulation of physical capital, human capital, productivity improvements, and hence income. Based on a globally representative dataset on patience in 76 countries, we study the implications of the model through a combination of reduced-form estimations and simulations. In the data, patience is strongly correlated with income levels, income growth, and the accumulation of physical capital, human capital, and productivity. These relationships hold across countries, subnational regions, and individuals. In the reduced-form analyses, the quantitative magnitude of the relationship between patience and income strongly increases in the level of aggregation. A simple parameterized version of the model generates comparable aggregation effects as a result of production complementarities and equilibrium effects, and illustrates that variation in preference endowments can account for a considerable part of the observed variation in per capita income.

JEL classification: D03, D90, O10, O30, O40.
Keywords: Patience; comparative development; factor accumulation.

*Armin Falk acknowledges financial support from the European Research Council through ERC # 209214. Dohmen, Falk: University of Bonn, Department of Economics; tdohmen@uni-bonn.de, armin.falk@uni-bonn.de. Enke: Harvard University, Department of Economics; enke@fas.harvard.edu. Huffman: University of Pittsburgh, Department of Economics; huffmand@pitt.edu. Sunde: University of Munich, Department of Economics; uwe.sunde@lmu.de.

1 Introduction

A long stream of research in development accounting has documented that both production factors and productivity play an important role in explaining cross-country income differences (Hall and Jones, 1999; Caselli, 2005; Hsieh and Klenow, 2010). By its nature, this line of work does not speak to the reasons why countries exhibit variation in these *proximate* determinants of comparative development. As a consequence, an active recent literature has investigated the *deep* determinants of development by studying the role of geography, climate, or history. While this line of work has included research on cultural factors such as trust, it is notoriously difficult to define and measure cultural variation.

A potential exception in this regard is heterogeneity in time preference, which has been argued to reflect deep cultural heterogeneity (Weber, 1930; Chen, 2013; Galor and Özak, 2016; Galor et al., 2016). A large number of dynamic neoclassical models highlight that both production factors and productivity ultimately arise from an accumulation process that requires future-oriented investments. Thus, in standard textbook models, the stocks of physical capital, human capital, or research intensity all crucially depend on the same structural parameter of time preference (e.g., Becker, 1962; Ben-Porath, 1967; Romer, 1990; Aghion and Howitt, 1992). Indeed, the role of heterogeneity in time preference has recently found renewed theoretical interest (e.g., Doepke and Zilibotti, 2014). However, perhaps due to the lack of meaningful data on time preference on a global scale, no empirical work has as yet studied the relationship between patience and development.

This paper fills this gap. The analysis is based on a simple OLG model in which individual- and country-level heterogeneity in patience affects the accumulation of physical capital, human capital, productivity, and hence income. The model delivers intuitive predictions, such as that individuals who exhibit higher patience save more, have a higher propensity to become educated, and have higher lifetime incomes. Analogous predictions hold at the country level. Moreover, the model allows us to investigate the quantitative magnitude of these effects at different levels of aggregation and to explore the role of aggregation effects due to general equilibrium mechanics.

We bring the model to the data by making use of the Global Preference Survey (GPS), a recently constructed global dataset on economic preferences from representative population samples in 76 countries (Falk et al., forthcoming). 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. 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 future-oriented decisions at the micro and macro levels.

Using these data, we study the relationship between patience, the accumulation of production factors and income at various levels of aggregation – across countries, subnational regions, and individuals – in reduced-form estimations and through a back-of-the-envelope calibration of the model. The empirical analysis begins by investigating the relationship between patience and comparative development as measured by (log) per capita income. In a univariate regression, average patience explains about 40% of the between-country variation in income (Falk et al., forthcoming). The reduced-form relationship is shown to be robust across a wide range of empirical specifications, which incorporate controls for many of the deep determinants previously identified in the empirical literature, such as geography, climate, the disease environment, or anthropological factors. Furthermore, in growth regressions, patience is significantly correlated with economic growth.

In the model, patience affects development through the accumulation of human capital, physical capital, and productivity. We hence proceed by investigating the correlations between patience and the proximate determinants of development. In the data, patience explains large fractions of the cross-country variation in capital stocks, savings rates, educational attainment, education expenditure, TFP, and research and development expenditure. These correlations are robust to the inclusion of a large and comprehensive vector of controls.

Next, we investigate whether the relationship between patience, human capital, and income extends to subnational analyses in which we can account for unobserved heterogeneity at the country level. This analysis exploits variation both across subnational regions and across individuals within regions. The regional-level analysis links average patience to average educational attainment and regional per capita income, akin to the approach taken by Gennaioli et al. (2013). 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. Analogous results prevail in individual-level analyses. Here, individual patience is significantly correlated with household income, savings behavior, and educational attainment within countries and regions. These within-country and within-region results arguably go a long way towards ruling out that variation in institutional quality or survey interpretation may confound the correlation between patience and income.

Both our theoretical model and the reduced-form analyses implicitly presume that patience *causes* the accumulation of production factors and hence income. However, a possible concern is endogeneity: measured patience might not reflect actual patience but instead be confounded by inflation, interest rates or the quality of the institutional environment. Similarly, patience may be endogenous to education. Clearly, perfect identification is difficult to achieve given the nature of the present research question. Still, the paper presents an array of empirical results that provide encouraging evidence that the correlation between patience and per capita income is not driven by the confounding effects of borrowing constraints, inflation and interest rates, institutional quality, life expectancy, educational attainment, or cognitive skills. For example, country-level patience remains strongly correlated with per capita income conditional on average years of schooling or the quality of the institutional environment.

In sum, patience is consistently linked to income and the accumulation of productive resources. At the same time, in the reduced-form analyses, the quantitative magnitude of the patience coefficient is substantially larger at the country level than at lower levels of aggregation. That is, while our individual-level regressions produce coefficient estimates that are in line with the micro literature on non-cognitive skills and preference heterogeneity (Dohmen et al., 2010; Huffman et al., 2017), this coefficient increases by a factor of seven in cross-country analyses. We evaluate whether this systematic difference in coefficient magnitudes can plausibly be generated by aggregation effects in general equilibrium. For this purpose, we leave the realm of OLS regressions and simulate a parsimoniously parameterized version of our equilibrium model. In this quantitative exercise, individuals and countries differ only in their patience. The results document that the effect of a shift in patience on income is much larger at the country level than at the individual level. These model-generated aggregation effects are in the same quantitative ballpark as those in the data. We further discuss and simulate measurement error and resulting attenuation bias as a potential driver of aggregation effects, but conclude that attenuation is unlikely to generate the observed patterns.

Our back-of-the-envelope calibration also showcases the model's ability to generate patience elasticities at the individual and aggregate levels that resemble those found in the data. We also perform a development accounting exercise and investigate how much of the empirical variation in per capita income can be explained by model-generated output variability, as induced by differences in patience. In these simulations, variation in patience accounts for a significant fraction of comparative development differences, even without imposing the assumption of exogenous technology differences to explain variation in stocks of production.

This paper contributes to a recent line of work that studies the effects of the human capital accumulation process on growth (Gennaioli et al., 2013; Squicciarini and Voigtländer, 2015). Several contributions have shown that more realistic representations of the human capital accumulation process and the corresponding effective stock of human capital 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 Sheshadri, 2014). These contributions require some initial and unexplained heterogeneity in TFP, however, in order to generate differences in human capital accumulation. Our paper contributes to this literature by providing micro evidence for one hitherto unexplored mechanism (preference heterogeneity) that may generate variation in human capital or TFP. In this sense, our paper also connects to the literature on the deep roots of development (e.g., Olsson and Hibbs Jr, 2005; Spolaore and Wacziarg, 2009; Algan and Cahuc, 2010; Ashraf and Galor, 2013; Alsan, 2015) and provides a natural link between this line of research and the branch focusing on development accounting and the role of factor accumulation for comparative development, complementing recent empirical work (e.g., Chen, 2013; Galor and Özak, 2016; Galor et al., 2016). 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). Finally, the paper connects to an active literature on the relationship between non-cognitive skills and life outcomes, which has often focused on the role of patience (e.g., Borghans et al., 2008; Alan and Ertac, 2018).

The remainder of the paper proceeds as follows. Section 2 presents the theoretical framework that underlies the empirical analysis. The data are described in Section 3. Section 4 investigates the reduced-form relationship between patience and aggregate development as well as the relation between patience and the proximate determinants. Section 5 presents the results at the subnational level. Section 6 assesses endogeneity concerns. Section 7 presents a quantitative assessment of the model and discusses the issue of aggregation effects, while Section 8 offers a concluding discussion.

2 Conceptual Framework

The basic hypothesis underlying this paper – that patience is linked to accumulation processes and hence development – directly follows from a long stream of prominent economic models, both micro and macro. For example, in a standard Ramsey–Cass–

Koopmans model, more patience implies a higher propensity to save, a higher steady state level of physical capital and income, as well as faster growth along the convergence path towards the steady state. The same is true in a human capital augmented model (Lucas, 1988), where greater patience also implies faster growth on the balanced growth path. Likewise, in the context of human capital theory, patience implies greater incentives to acquire education (Becker, 1962; Ben-Porath, 1967). In terms of residual productivity, endogenous growth theory suggests that more patience raises the present value of R&D and hence increases research intensity (Romer, 1990; Aghion and Howitt, 1992).[1]

Our model represents a simple extension of this prior work. The main benefit of the extended model is that it allows for a quantification in which patience is linked to the accumulation of multiple accumulation factors, at different levels of aggregation. We outline the model and its main implications here, but relegate detailed derivations to Appendix B.

Setup. Consider an economy of overlapping generations of individuals that live for two periods. Each generation has unit mass and each period lasts for one unit of time. When young, all individuals work as unskilled workers in production and choose the fraction of labor earnings they want to consume and save. 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 youth fully depreciates at the end of their second period of life. During their youth, individuals make decisions regarding their education: they can decide to remain unskilled workers or to become educated workers during the second period of their life.

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

$$U^i = \ln c_t + \beta^i \ln c_{t+1}\,, \tag{1}$$

where $0 < \beta^i < 1$ is the discount factor of individual i that reflects i's patience. Individuals differ in their patience. For analytical convenience, β^i is modeled as a draw from a uniform distribution $\beta^i \sim U[\chi - \epsilon; \chi + \epsilon]$, where $\chi > 0$ reflects the average level of patience in a given country (with $\epsilon > 0$, $\chi > 0$ and $0 < \chi - \epsilon < \chi + \epsilon < 1$). Variation in β^i conditional on χ captures individual-level heterogeneity within an economy.

[1] 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.

Human Capital Acquisition. The acquisition of education takes a fraction $(1-\psi)$ of the first period of life. We assume that the effectiveness of time spent on education increases with patience, so that an individual with patience β^i accumulates a stock of human capital $h(i) = \beta^i e^{\rho(1-\psi)}$, which corresponds to the usual Mincerian specification with $\rho > 0$ as parameter for the return. Imposing the assumption that the effectiveness of time devoted to education increases with patience has both substantive and technical rationales. First, from a substantive viewpoint, a growing body of micro evidence demonstrates that children with greater patience are indeed more effective in school, as measured by fewer disruptions and "behavior grades" (e.g., Sutter et al., 2013; Alan and Ertac, 2018). From a technical perspective, the assumption serves the purpose of breaking the well-known separation theorem.[2]

Budget Constraints. Denote the wage of unskilled workers by w_t^W, the earnings of an educated worker as w_t^E, the savings rates of unskilled and educated workers as s_t^W and s_t^E, and the return on capital as R_t. The respective budget constraints are then

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

$$\text{educated:} \quad c_t^y = w_t^W \cdot (1 - s_t^{iE}) \cdot \psi, \qquad c_{t+1}^o = w_{t+1}^E \cdot h_t(i) + w_t^W \cdot s_t^{iE} \cdot \psi \cdot R_{t+1} \tag{3}$$

Individuals take wages and capital returns as given.

Production. Output can be used for consumption or capital accumulation, and is produced using capital, unskilled labor and educated labor. The production of final output Y during period t takes the form

$$Y_t = A_t K_t^{\alpha} \left[L_t^{\frac{\sigma-1}{\sigma}} + H_t^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma(1-\alpha)}{\sigma-1}}, \tag{4}$$

where the aggregate capital stock in period t is K_t, the stock of unskilled labor is denoted by L_t, and the effective stock of educated labor is H_t, with $0 < \alpha < 1$ and $\sigma > 1$. Factors are remunerated on competitive markets for capital, and for unskilled and educated labor, respectively.

Factor Market Clearing. In this environment, only individuals with β^i larger than a threshold level of patience $\tilde{\beta}_t$ optimally decide to become skilled. In each generation,

[2]Otherwise, in an environment such as the one described here, where savings allow for consumption smoothing, education choices do not interfere with intertemporal trade-offs and only maximize lifetime income. This assumption therefore essentially parallels the assumption of incomplete capital markets in models without savings and physical capital, see, e.g., Doepke and Zilibotti (2014) and Klasing and Milionis (2014).

this implies a share of skilled individuals of $\lambda_t = \frac{\chi+\epsilon-\tilde{\beta}_t}{2\epsilon}$. Since unskilled workers of two generations coexist at each point in time, the stock of unskilled labor is given by $L_t = (1-\lambda_{t-1}) + (1-\lambda_t) + \psi\lambda_t$. Correspondingly, the stock of educated labor in a given period is given by $\lambda_{t-1}(\chi + \epsilon - \lambda_{t-1}\epsilon)e^{\rho(1-\psi)}$.

The average level of patience of unskilled workers in cohort t is then given by $\underline{\beta}_t = \chi - \lambda_t \epsilon$. Likewise, the average patience of educated workers is $\bar{\beta}_t = \chi + (1-\lambda_t)\epsilon$. Since individual savings differ across education groups and depend on individual patience, the information about the population composition allows for the determination of aggregate capital accumulation. During the second period of their lives, educated workers supply their human capital and earn a skill premium $\eta_t = \frac{w_t^E}{w_t^S} = \left(\frac{L_t}{H_t}\right)^{1/\sigma}$.

Externalities and Growth. In its basic form, the model does not feature any feedback of patience on factor productivity or growth. However, the model can easily be extended to accommodate both features by imposing the additional assumption of a human capital externality of the stock of educated workers on productivity or productivity growth. In particular, we apply a simplified version of a human capital externality on productivity (e.g., Lucas, 1988) for TFP, with $A_t = \bar{A} \cdot (1 + H_t)^{\theta}$. Likewise, in model extensions we consider a mechanism along the lines of Nelson and Phelps (1966), according to which a larger share of educated workers in the population is conducive to productivity growth,

$$g_t = \frac{A_{t+1} - A_t}{A_t} = \lambda_t^{\phi} \tag{5}$$

where $\phi > 0$. For most of the analysis, we will abstract from TFP externalities and growth, i.e., set $\theta = \phi = 0$.

Equilibrium. The steady state equilibrium of the model is characterized by a cut-off level of patience, $\tilde{\beta}$, that splits the population into unskilled workers (with a level of $\beta < \tilde{\beta}$) and educated entrepreneurial workers (with $\beta > \tilde{\beta}$). This cut-off depends on parameters $\{\alpha, \sigma, \psi, \rho\}$ (and in the extensions on $\{\theta, \phi\}$) and is unique and interior.[3]

Predictions. Our empirical exercises – both reduced-form and quantitative – exploit heterogeneity in patience at the individual and at the country level. The thought experiment that the model and our analyses address is how income and factor accumulation respond to a change in patience (either individual or average), all else equal.

[3] See Appendix B for details.

At the individual level, aggregate allocations and prices are fixed. Under mild parameter restrictions discussed in Appendix B, the model delivers the predictions that higher levels of patience lead to (i) higher savings; (ii) a higher propensity to acquire human capital; and (iii) higher lifetime income.

At the country level, allocations and prices are no longer fixed. The thought experiment is now to compare two economies that are otherwise identical, yet differ in their average level of patience, χ. Again under mild parameter restrictions discussed in Appendix B, the model predicts that higher average patience leads to (i) higher aggregate savings and capital stocks; (ii) a larger population share with high education; (iii) higher GDP per capita; and (iv) in the extended version of the model with $\theta > 0$ and $\phi > 0$, higher productivity and faster growth.

In addition, the model allows for the exploration of the relative size of the effects of variations in patience at the individual and aggregate level. As discussed in more detail below in Section 7, the model delivers quantitatively larger effects at higher levels of aggregation as a consequence of general equilibrium mechanics.

In the remainder of the paper, we take the model to the data in two steps. First, we investigate the empirical validity of the qualitative predictions of the model on the basis of reduced-form OLS regressions at three levels of aggregation: across individuals within subnational regions, across subnational regions within countries, and across countries. Second, we conduct a quantitative analysis using a parameterized version of the model.

3 Data

Conducting an empirical analysis that links comparative development to patience requires reliable data on patience from representative population samples for a broad set of countries. We use novel data on patience contained in the Global Preference Survey (GPS), a data set on economic preferences from representative population samples in 76 countries. In many countries around the world, the Gallup World Poll regularly surveys representative population samples about social and economic issues. We created the GPS by adding a set of survey items that were explicitly designed to measure a respondent's time preferences, risk preferences, social preferences, and trust, as part of the regular 2012 questionnaire (for details see Falk et al., forthcoming).

Four features make these data suited for the present study. First, the preference measures have been 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 1,000 participants per country, for a total of 80,000 participants 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 and finally, 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., 2015). 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 the 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. (forthcoming) 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 and make 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.[4] As described in detail in Falk et al. (2015), 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 considerable methodological advance compared to the often ad-hoc selection of questions for surveys based on introspective arguments about plausibility or relevance.

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 fact, it turns out that the relationship between patience and comparative development is mostly driven by this quantitative measure. In our reduced-form estimations we make use of the composite patience measure as it was developed in the experimental validation procedure. While this patience measure has the advantage of being free of assumptions, it has the disadvantage that it cannot be easily interpreted in terms of a discount factor. Thus, to explore a more quantitative interpretation, in Section 7.2, we hence transform the patience variable into a discount factor for the purpose of a quantitative exercise.

[4]Specifically, responses to both items were standardized at the individual level and then aggregated:

$$\text{Patience} = 0.7115185 \cdot \text{ Staircase measure } + 0.2884815 \cdot \text{ Qualitative measure.}$$

These weights are based on OLS estimates of a regression of observed behavior in financially incentivized laboratory experiments on the two survey measures. See Falk et al. (2015, forthcoming) for details.

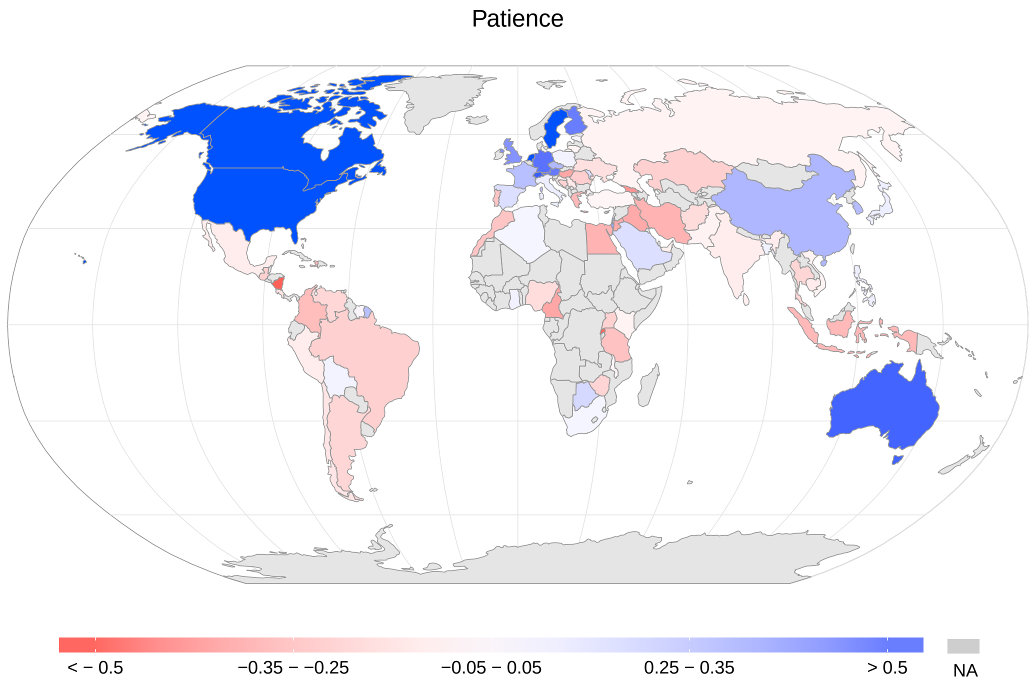

Figure 1: Distribution of patience across countries

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 region, or a country. Figure 1 depicts the resulting distribution of patience across countries, relative to the world's average individual level. 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.

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.

4 Cross-Country Evidence

4.1 Patience and Contemporary Development

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, implying that patience alone "explains" about 39% of the variation in log income per capita; also see Falk et al. (forthcoming). Columns (2) through (4) successively add a comprehensive set of geographic and climatic covariates. Column (2) contains controls for world regions.[5] Column (3) contains additional controls for absolute latitude, longitude, the fraction of arable land, land suitability for agriculture, and the timing of the Neolithic transition. Column (4) adds average precipitation and temperature as well as the fractions of the population that live in the (sub-) tropics or in areas where exists the risk of contracting malaria. Finally, column (5) additionally controls for trust, and genetic diversity and its square. While the inclusion of this large vector of covariates reduces the coefficient of patience by about 25%, the coefficient remains statistically significant and quantitatively large. At the same time, 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), adds little to the explanatory power once patience is included in the analysis. Figure 2 illustrates the conditional relationship for the estimates of column (5).

Appendix E presents two sets of robustness checks. First, Table 12 documents that controlling for average risk aversion, legal origin dummies, ethnic, religious, and linguistic fractionalization, major religion shares, the fraction of European descent, the genetic distance to the US, and other geographical variables, does not affect our main result. Second, Table 13 documents that the relationship between patience and per capita income robustly appears in various sub-samples, i.e., within each continent, within OECD or non-OECD countries, or within former colonies and countries that have never been colonized.

4.2 Patience and Factor Accumulation

In the model, the reduced-form relationship between patience and development operates through accumulation processes. In this section, we investigate whether the 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.

Table 1: Patience and national income

	Dependent variable: Log [GDP p/c]				
	(1)	(2)	(3)	(4)	(5)
Patience	2.32***	1.84***	1.62***	1.55***	1.70***
	(0.23)	(0.24)	(0.31)	(0.31)	(0.29)
Distance to equator			0.014	0.0041	-0.025
			(0.01)	(0.02)	(0.02)
Longitude			0.0010	0.0051	0.0075
			(0.01)	(0.01)	(0.01)
Percentage of arable land			-0.023**	-0.013	-0.0096
			(0.01)	(0.01)	(0.01)
Land suitability for agriculture			0.46	-0.089	0.14
			(0.64)	(0.50)	(0.46)
Log [Timing neolithic revolution]			0.59	0.36	0.34
			(0.36)	(0.30)	(0.31)
Average precipitation				0.0065	0.0021
				(0.00)	(0.00)
Average temperature				0.044*	0.017
				(0.02)	(0.03)
% living in (sub-)tropical zones				-1.16*	-1.04*
				(0.67)	(0.60)
% at risk of malaria				-1.41***	-1.38***
				(0.48)	(0.44)
Predicted genetic diversity					522.4***
					(132.02)
Predicted genetic diversity sqr.					-372.7***
					(96.83)
Trust					-0.18
					(0.43)
Continent FE	No	Yes	Yes	Yes	Yes
Observations	76	76	74	74	74
R^2	0.39	0.69	0.73	0.81	0.85

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

are consistent with patience affecting income through the "channels" of human and physical capital as well as (residual) factor productivity. To this end, we investigate whether patience is related to the levels of production factors and productivity as well as the corresponding accumulation flows.

Physical Capital. To comprehensively 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

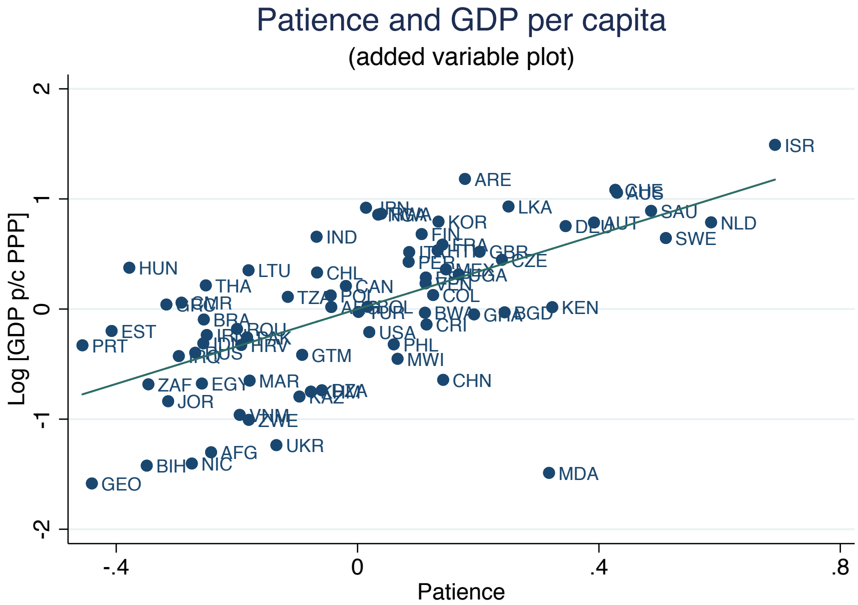

Figure 2: Patience and national income (added variable plot conditional on the full set of covariates in column (5) of Table 1).

of the unconditional relationship and of the relationship conditional on the extensive set of baseline 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 respective 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. These data 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 arguably noteworthy, given the similarity of this subset of countries in terms of economic development and other characteristics.

Human Capital. As measures of human capital, we consider proxies for both the quantity and quality of schooling, as well as investments into education. Our dependent

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***	1.12***	7.43***	9.19***	6.08**	8.36**	8.52***	9.80***
	(0.27)	(0.28)	(2.41)	(3.31)	(2.34)	(3.53)	(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	0.37	0.04	0.43	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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Patience and human capital

	Dependent variable:							
	Yrs. of schooling		% Educated		Cognitive skills		Educ. exp. (% GNI)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patience	4.34***	2.43***	38.5***	19.9***	0.81***	0.36*	1.69***	1.32**
	(0.58)	(0.86)	(5.45)	(7.41)	(0.13)	(0.20)	(0.37)	(0.61)
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	49	48	74	73
R^2	0.34	0.76	0.30	0.73	0.28	0.76	0.14	0.54

OLS estimates, robust standard errors in parentheses. The percentage educated is the percentage that has at least secondary education Barro and Lee (2012). See column (5) of Table 1 for a complete list of the additional controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

variables are (i) average years of schooling; (ii) the fraction of the population aged over 25 that has at least secondary education (Barro and Lee, 2012); (iii) cognitive skills derived from educational achievement tests (Hanushek and Woessmann, 2012); (iv) and education expenditure as percentage of national income.

Table 3 reports the results. Columns (1) and (2) reveal a positive relation between patience and average years of schooling. The explained variation of roughly 30% indicates a strong unconditional relationship, which holds up when controlling for the baseline set of covariates. Columns (3) through (8) present the analogous results for the four alternative measures of human capital. We find a significant positive relationship of patience with all human capital proxies, both stocks and flows.

Table 4: Patience, productivity and R&D

	Dependent variable:					
	TFP		R&D exp. (% GDP)		Log [# Researchers in R&D]	
	(1)	(2)	(3)	(4)	(5)	(6)
Patience	0.29***	0.16**	2.10***	1.92***	2.70***	1.43***
	(0.05)	(0.07)	(0.24)	(0.49)	(0.35)	(0.50)
Continent FE	No	Yes	No	Yes	No	Yes
Additional controls	No	Yes	No	Yes	No	Yes
Observations	59	58	60	59	69	68
R^2	0.29	0.71	0.54	0.72	0.35	0.83

OLS estimates, robust standard errors in parentheses. Number of researchers in R&D are per 1,000 population. Columns (1) and (2) 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3 Patience, Productivity, and Growth

In the extensions of the model in Section 2, patience affects productivity levels and productivity growth through human capital externalities. We first study the relationship between patience and productivity (accumulation) along these lines by considering (i) a standard measure of total factor productivity; (ii) the share of GDP made up by R&D expenditures; and (iii) the number of researchers in R&D (per 1,000 inhabitants).

Table 4 contains the respective estimation results. Patience is uniformly linked to the stock of productivity and corresponding accumulation processes. These results hold in both unconditional and conditional regressions.

We next investigate the relationship 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. The results are presented in Table 5. The first column shows the unconditional correlation between growth since 1950 and patience. The second column includes controls for log per capita income in the base year to capture convergence dynamics, and continent fixed effects. Column (3) adds the controls from column (4) in Table 1. Columns (4)–(6) present analogous results for growth in 1975. For both base years, higher levels of patience are significantly associated with higher growth rates.

Table 5: Patience and economic growth

	Dependent variable: Annual growth rate in GDP p/c (in %) since...					
	1950			1975		
	(1)	(2)	(3)	(4)	(5)	(6)
Patience	0.83**	1.00**	1.26***	0.75*	1.42***	1.96***
	(0.32)	(0.41)	(0.32)	(0.41)	(0.40)	(0.44)
Log [GDP p/c base year]		-0.81***	-1.19***		-1.02***	-1.66***
		(0.22)	(0.20)		(0.19)	(0.27)
Continent FE	No	Yes	Yes	No	Yes	Yes
Additionals controls	No	No	Yes	No	No	Yes
Observations	62	62	62	68	68	67
R^2	0.09	0.54	0.81	0.04	0.57	0.75

OLS estimates, robust standard errors in parentheses. See column (5) of Table 1 for a complete list of the additional controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Subnational Evidence

5.1 Patience and Development Across Subnational Regions

We proceed by considering variation across sub-national regions. The individual-level patience data in the GPS contain regional identifiers (usually at the state or province level). This 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.[6] 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. For example, potential concerns about the role of language and institutions for survey responses are less relevant in within-country analyses.

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 for some regions. 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 literature (Chetty and Hendren, 2016) and shrink regional patience to the sample

[6]See Appendix C for an overview of the number of regions per country.

mean by its signal-to-noise ratio. Specifically, shrunk patience of region j, β_j^s, is computed as a convex combination of observed average patience in region i, β_j, and the mean $\bar{\beta}$ of the region sample averages β_j:

$$\beta_j^s = w_j \beta_j + (1 - w_j)\bar{\beta} \tag{6}$$

where the region-specific weights are given by

$$w_j = \frac{Var(\beta_j) - E[se_j^2]}{Var(\beta_j) - E[se_j^2] + se_j^2} \tag{7}$$

Here, $Var(\beta_j)$ is the variance of the regional means and se_j the standard error of β in region j. This shrinkage procedure has an explicit Bayesian interpretation according to which observations with high noise (e.g., due to small N) are shrunk further towards the sample average.

Table 6 reports regression results for average education and average per capita income 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 mirror those established in the country-level analysis: we find significant relationships between patience and per capita income, and between patience and human capital, conditional on country fixed effects.[7]

A noteworthy result in Table 6 is that the patience coefficient drops by a factor of seven once country fixed effects are included (columns (2) and (5)). We will return to this observation below when we discuss the role of aggregation effects.

5.2 Individual Patience, Accumulation and Income

In a final step of the analysis, we investigate the individual-level predictions from Section 2. This analysis is based on data on individual income, savings and educational attainment in the GPS. Studying the relationship between patience and factor accumulation at the individual level further allows us to control for unobserved heterogeneity at the regional level.

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

[7] The results are quantitatively very similar if we do not exclude any regions and implement the shrinkage procedure on the full sample.

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 country level) in parentheses. Patience is shrunk patience, see equation (6). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 educated. This pattern holds conditional on a comprehensive vector of individual-level covariates including age, age squared, gender, religion fixed effects, 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 F).

At the same time, as we discuss in detail in section 7 below, the patience coefficient again becomes considerably smaller once country fixed effects are accounted for. This pattern closely resembles the results of the regional-level analysis. For instance, in regressions with log income per capita as dependent variable, the OLS coefficient of patience drops by a factor of about seven once country fixed effects are included, both in the individual- and the cross-regional level analyses.

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
Regional 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 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 F for a detailed description of all dependent variables. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

6 Adressing Endogeneity Concerns

While the model in Section 2 implicitly presumes a causal role of patience for accumulation processes and income, a causal interpretation of our empirical results is subject to some potential criticisms: (i) the patience variable might not measure "actual" patience, but rather "revealed" patience, which includes features of the external environment such as institutions, constraints, or interest rates; and (ii) that our patience variable may measure "actual" patience, yet the OLS correlations be driven by omitted variables or reverse causality.

We do not purport that our paper rules out all potential endogeneity concerns. Rather, we view this paper as a first contribution that studies the systematic relationship between patience, accumulation and income documenting a novel set of stylized facts. Nonetheless, this section takes a more nuanced look at the data by investigating the extent to which the main cross-country result 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 face upward sloping income profiles and are borrowing constrained. To address this issue, we exploit the idea that borrowing constraints are likely to be less binding for relatively affluent people. We hence employ the average patience of each country's top income quintile as an explanatory variable. As shown in column (1) of Table 8, 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 8.

Subjective Uncertainty. If respondents face subjective uncertainty in our quantitative decision task, people might seem more impatient than they really are. To check whether this drives the findings, we condition on both objective and subjective measures of the quality of the institutional environment as well as people's life expectancy.

Table 8: Patience and per capita income: Robustness

	Dependent variable: Log [GDP p/c PPP]						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Patience of top income quintile	1.60***						
	(0.19)						
Patience		2.00***	0.77***	1.52***	1.04***	1.17***	
		(0.33)	(0.27)	(0.41)	(0.24)	(0.24)	
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)	
Patience (binarized staircase)							4.78***
							(0.68)
Continent FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76	59	72	59	76	72	76
R^2	0.69	0.64	0.79	0.69	0.81	0.77	0.66

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

First, in column (3) of Table 8 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 their institutional environment. A first composite index incorporates people's confidence in the national government, the legal system and courts, the honesty of elections, and the military. An additional item elicits people's confidence in the country's financial institutions and banks, and thus arguably captures a dimension of financial uncertainty as it applies to our survey items. 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.

Education. Our survey requires respondents to think through abstract choice problems, which might be unfamiliar and cognitively challenging for some participants. This

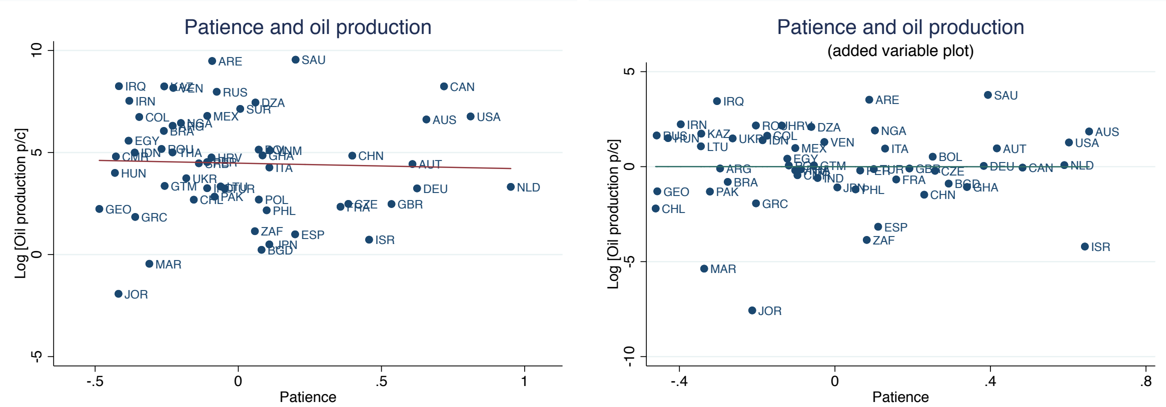

Figure 3: Patience and oil production per capita (in 2014 Dollars). The left panel depicts the raw correlation between log oil production per capita and patience ($\rho = -0.04$), while the right panel contains a plot conditional on the full set of baseline covariates in column (5) of Table 1.

could induce people to decide based on heuristics, perhaps due to low education. Column (6) of Table 8 regresses GDP per capita jointly on patience and average years of schooling, and patience remains highly significant and large in magnitude. Finally, column (7) 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 perhaps helpful way of investigating the plausibility of such an account is to examine the relationship 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 3 plots the raw correlation between log oil production per capita (measured in 2014 Dollars) and patience. The two variables are uncorrelated ($\rho = -0.04$). The right panel depicts the partial correlation conditional on the full set of controls in column (5) of Table 1. While these results do not rule out a causal link between income and patience, they provide an initial piece of evidence that the patience variable picks up variation that is independent of income effects.

7 Patience and General Equilibrium Effects

As highlighted in the discussion of the model in Section 2, the comparative statics prediction regarding the effect of an increase in individual-level patience on individual income is obtained under the (implicit) assumption that prices are fixed and the aggregate allocation is unchanged. In the empirical analysis, this is mirrored in individual-level regressions that include country fixed effects. At higher levels of aggregation, the patience coefficient corresponds to a shift in the (mean of the) distribution of the patience parameter. Here, factor allocations and prices are no longer fixed, and the corresponding regressions compare across steady states. In other words, the estimates at the aggregate level might also reflect general equilibrium effects.

This section explicitly investigates the role of general equilibrium effects through a combination of reduced-form and calibration exercises. These exercises focus on two issues: (i) potential aggregation effects, i.e., differences in patience coefficient magnitudes across levels of aggregation; and (ii) the implications of general equilibrium effects for individual decision-makers.

7.1 Reduced-Form Patterns

7.1.1 Aggregation Effects

Throughout the entire reduced-form 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 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 that drops to 0.05 when country fixed effects are included. A different way to look at this pattern is that – in both the regional- and individual-level regressions – the patience coefficient drops by a factor of roughly seven once country fixed effects are included.

It is worth pointing out that 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 usage of different patience measures and income variables, the few benchmarks that we have reveal encouraging similarities. In the nationally representative German sample of Dohmen et al. (2010), the coefficient of (the z-score of) patience in a regression with log per capita income 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.

Table 9: Reduced-form analysis: Country patience and individual outcomes

	Dependent variable:					
	Log [HH income p/c]		Saved last year		1 if at least sec. educ.	
	(1)	(2)	(3)	(4)	(5)	(6)
Individual patience	0.051^{***}	0.051^{***}	0.039^{***}	0.030^{***}	0.035^{***}	0.013^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Average patience in country	2.10^{***}	1.35^{***}	0.28^{*}	0.12	0.19^{***}	0.14^{***}
	(0.21)	(0.18)	(0.14)	(0.12)	(0.05)	(0.04)
Individual-level controls	No	Yes	No	Yes	No	Yes
Continent FE	No	Yes	No	Yes	No	Yes
Observations	79245	69508	15260	14488	79357	69718
R^2	0.27	0.51	0.03	0.07	0.04	0.20

Individual-level OLS estimates, standard errors (clustered at country level) in parentheses. Individual-level controls include age, age squared, gender, subjective math skills, and religion fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.1.2 Effects on Individuals

General equilibrium effects, if present, point to the importance of the cultural environment in which individuals make their decisions. That is, an individual's optimal decisions and their income might depend not only on their own patience, but also on the average patience within an economy.

Table 9 empirically investigates the relationship between individual decisions and income on the one hand, and both individual and country-level patience on the other hand. The results reveal that individual income and individual education decisions are not only positively related to individual patience, but also to the average level of patience within an economy. For savings, the effect is positive, but quantitatively much smaller and insignificant. This is consistent with the theoretical prediction of two opposing effects. These patterns provide a first indication that the broader cultural environment in which individuals make their decisions has direct effects at the individual level.

In summary, the data exhibit (i) strong aggregation effects and (ii) a systematic relationship between country-level patience endowments and individual decisions and income. We now examine whether a calibration of our model delivers comparable results.

7.2 A Quantitative Assessment

7.2.1 Setup

Approach. In our quantitative exercise, we conduct the same thought experiments as in the reduced-form analyses, i.e., we vary (i) individual patience while holding the aggregate allocation constant, and (ii) average country patience. We then compare the simulated effects and with those observed in the data.

To keep this analysis directly comparable to the reduced-form patterns, we shift individual patience by one standard deviation (as in the individual-level OLS regressions, in which patience was standardized into a z-score). Likewise, we shift country patience by one standard deviation in terms of the individual-level variation, which again directly corresponds to the OLS point estimates. In the cross-country data, a one-standard-deviation increase (in terms of the individual-level variation) in patience corresponds almost exactly to the difference between the 10th and 90th percentile of the cross-country patience distribution.

Parameter Assumptions. Quantifying the model requires assumptions about several parameters, in particular about the patience parameter χ (the mean of the cross-country distribution). It is widely known in the experimental and behavioral economics literatures that the mapping of experimental choices into a particular *level* of a discount factor is challenging since, inter alia, (i) the curvature of the utility function is unobserved; (ii) respondents' lifetime wealth is unknown; and (iii) respondents might partially narrowly bracket the experimental choice without fully taking lifetime wealth into account.

To sidestep these issues, we assume a reasonable discount factor for the impatient economy and then scale the patience level of the patient economy relative to the impatient economy using the GPS data. Specifically, we assume that the annual average discount factor of the impatient economy (the 10th percentile of the patience distribution) is given by $\beta_l = 0.96$, which implies a 25-year discount factor of $\chi \approx 0.37$. Appendix B.3 discusses in detail how this parameter assumption pins down an annual discount factor of the patient economy (the 90th percentile of the patience distribution) of $\beta_h = 0.975$, which implies $\chi_h \approx 0.57$. Thus, in the calibration experiment, we separately shift individual-level patience by one standard deviation of 0.2 and country-level patience from $\chi = 0.37$ to $\chi = 0.57$.

Table 10 summarizes and justifies all remaining parameter assumptions. Appendix B.3 presents a more detailed discussion.[8]

[8] In the baseline specification, we abstract from human capital externalities on TFP and TFP growth, i.e., $\theta = \phi = 0$. To illustrate the implications of these externalities, in extensions we assume $\theta = 0.3$ and $\phi = 0.61$.

Table 10: Parameter assumptions

Parameter	Interpretation	Explanation
$\chi_l = 0.37$	Impatient 25-year discount factor ($\beta_l = 0.96$)	Exogenously set
$\chi_h = 0.57$	Patient 25-year discount factor ($\beta_h = 0.975$)	Scaled relative to χ_l with GPS data
$\epsilon = 0.3$	Within-country variation in patience	From GPS data
$\alpha = 0.4$	Capital income share	IMF
$\sigma = 1.4$	Elasticity of substitution	Acemoglu and Autor (2011)
$1 - \psi = 0.24$	Fraction of time required to become skilled	Requirement of six additional years for becoming skilled (Caselli, 2017)
$\rho = 2$	Scale parameter for human capital	Caselli (2017)

Computation of Effect Sizes. To ensure comparability between the empirical analysis and the quantitative version of the model, the effects of a one-standard-deviation variation in patience on income, on the fraction of skilled workers, and on savings rates are computed as the average of the marginal effects for unskilled and skilled workers in the two model economies, weighted by the corresponding population shares, averaged across the two economies. The country-level model analyses are obtained by a comparison of the corresponding steady state values of income, capital, and skill shares in the two economies.

As empirical moments, we use coefficient estimates for the marginal effect of an increase in patience by one standard deviation in terms of the total individual-level variation. We compare the theoretical effect sizes with the coefficients from analyses with and without covariates, as in the respective empirical analyses described above; see the table notes for details.

7.2.2 Results

Aggregation Effects. Table 11 presents the results of two alternative comparative statics exercises. First, we evaluate the effect of increasing individual-level patience by one standard deviation (from $\chi_l = 0.37$ to χ_h=0.57), while holding the aggregate allocation constant. Second, we evaluate the effect of increasing average patience in an economy by the same amount. In this second analysis, we compare economies across steady states, so that the overall allocation changes. We perform both of these analyses in our parameterized model and compare the results with the regression coefficients given above.

We consider three versions of the model: (i) one without TFP externalities and growth; (ii) one with a TFP externality; and (iii) one with TFP and growth externalities.

The simulation results indicate that variation in patience induces substantial vari-

Table 11: Quantified model vs. data

	Effect of 1 SD increase of patience ($\chi = 0.37 \rightarrow \chi = 0.57$)				
	Model			Data	
	Baseline	TFP externality	TFP externality & growth	No controls	Controls
	(1)	(2)	(3)	(4)	(5)
	Individual level				
Per capita income	0.04	0.04	0.04	0.05	0.04
Fraction skilled	0.04	0.04	0.04	0.07	0.04
Savings	0.03	0.03	0.03	0.04[a]	0.03[a]
	Country level				
Per capita income	1.28	1.50	1.46	2.32	1.70
Fraction skilled	0.25	0.25	0.26	0.39	0.20
Savings	2.00	2.16	2.06	1.93	1.12
TFP		0.16	0.16	0.29	0.16
Growth			2.16	0.75	1.96

Notes. The effect sizes in the simulated model are computed as follows. At the individual level, the estimated effect of variation in patience on savings, fraction of skilled labor, and income is computed as the average of the marginal effects for unskilled and skilled workers in the two economies, weighted by the corresponding population shares and evaluated for a one-standard-deviation shift in patience, averaged across countries. The country-level model analyses are obtained by a comparison of the steady states of the two economies that correspond to the 10th and 90th percentile of the cross-country patience distribution (a one-standard-deviation difference), respectively. The effect sizes in the data at the country level correspond to the OLS coefficients without covariates and with all controls from column (5) in Table 1, respectively. At the individual level, the effect sizes correspond to analyses with country fixed effects, either without additional covariates, or including the covariates in column (4) of Table 7. In the country-level analysis, the fraction of skilled workers is the secondary and tertiary enrolment rate. In the corresponding individual-level analysis, the fraction of skilled workers refers to the probability of having at least secondary education.

[a] In the theoretical model, savings rates are a continuous variable. Due to the assumption of log utility, everybody saves a strictly positive amount, so that only the intensive margin of savings is relevant. In the data, we only have access to the extensive margin, i.e., whether a household saved or not. To the extent that the intensive margin of savings rates is increasing in patience, our estimates of 0.04 or 0.03 hence constitute a lower bound.

ation in income across countries. Specifically, the difference in patience between two countries with $\chi_l = 0.37$ and $\chi_h = 0.57$ implies an income gap whereby the former country has an almost 25% lower income per capita in equilibrium.

Overall, the coefficient estimates and the size of the aggregation effect in the data are broadly consistent with the predictions of the parameterized version of the model.

At the individual level, shown in the upper panel of the table, the estimated effect of variation in patience on savings, the probability of having at least secondary education, and income can approximately be replicated by the model (compare columns (1), (2), and (3) to (4) and (5)).

Comparing across steady states, similar results hold, as shown in the lower panel of the table. Most importantly, the model generates substantial aggregation effects. Comparing the results of the baseline model (column (1)) across the two panels of the table, the model generates an amplification of factor 36 for income, factor 58 for savings, and factor 7 for the share of skilled workers, which roughly corresponds to the amplification observed in the data. These simulation results illustrate that equilibrium effects can account for the quantitative differences in the estimates across different levels of aggregations. These 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).

Our quantitative analysis documents that aggregation effects might arise purely through general equilibrium effects. It is conceivable (and perhaps likely), however, that additional aggregation effects are generated by externalities of human capital or institutions. For instance, when patient populations opt for institutions designed to foster long-term growth as opposed to short-term rent extraction, these institutions might impose additional positive effects on human and physical capital accumulation. This argument complements evidence that the effect of education on income is substantially larger at an aggregate level (Gennaioli et al., 2013) as well as the view that productivity differences might have indirect effects through their influence on factor accumulation (Hsieh and Klenow, 2010; Manuelli and Sheshadri, 2014).

Effects on Individuals. The model also allows for an analysis of how individual income depends on the cultural background (average patience), while fixing individual patience and individual decisions. For instance, an individual with $\beta^i = 0.37$ decides to be unskilled in both simulated economies with $\chi_l = 0.37$ and $\chi_h = 0.57$. Still, the income of this individual is more than 8% higher in the country with $\chi_h = 0.57$. The same is true for a hypothetical individual with $\beta^i = 0.67$ who would optimally decide to be skilled in both countries and earn an income that is more than 10% higher in the country with χ_h=0.57. These patterns highlight how general equilibrium effects in combination with variation in aggregate patience directly affect individual well-being.

7.2.3 Development Accounting

The model quantification also allows this study to speak to a focus of much of the recent literature, i.e., how the neoclassical model can account for the massive observed income (output) differences across countries. In the data underlying our study, the ratio of per capita income of the 90th to the 10th percentile is 47. As documented in the literature, the neoclassical model typically requires large TFP differences between these countries to account for these 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 difference in TFP that is required to explain the income gap.[9]

In order to generate the 47-fold income gap in our data, our baseline model requires a 12.9-fold difference in TFP.[10] It is worth emphasizing that TFP is completely neutral for the education decision in our setting. This implies that, by construction, there is no compounding of TFP-differences by its influence on individual decisions, but only through the demand and supply of capital. Obviously, extending the model to account for the insights of the literature on more realistic human capital accumulation processes, for instance by considering skill-augmenting technology differences, would allow for the TFP differences required to explain income variation to be even smaller.

7.3 The Role of Measurement Error

The difference in coefficients between the country and individual level might be driven by differences in attenuation bias. The relationship between individual income and patience should be more attenuated if individual patience is measured with more noise than country-level patience (as is likely the case). To assess the quantitative relevance of this explanation, we conduct simulations that provide an estimate of the extent of measurement error that is required to generate the observed variation in coefficient magnitudes across different levels of aggregation. More specifically, suppose that observed patience β_o is given by $\beta_o = \beta_{true} + a \times \varepsilon$, where β_{true} is the respondent's true patience, a a scaling parameter and $\varepsilon \sim \mathcal{N}(0,1)$ a noise term (recall that observed

[9]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 Sheshadri (2014) find that accounting for human capital accumulation differences in human capital substantially amplifies TFP differences across countries. Schoellman (2012) makes a related point based on a novel methodology designed to measure differences in human capital quality.

[10]To obtain this result, we first simulate the model for $\chi = 0.37$ imposing the level of TFP that is required to deliver a level of output per capita that is comparable to that observed in the data for the 10th percentile. Then, we simulate the model for $\chi = 0.57$ and compute the level of TFP that is required to account for the unexplained gap in output.

patience is also normalized to have a mean of zero and a standard deviation of one, so the noise term has the same variation as patience). The simulations, described in detail in Appendix D, show that $a = 6$ 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., 2011), yet $a = 6$ would imply a test-retest correlation of only $= 0.02$.[11] 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 (see, e.g., Falk et al., 2016).

In sum, the results suggest that the strong increase in the magnitude of the relationship between patience and income is not spurious, but driven by indirect general equilibrium effects or production factor externalities that play out at the country level.

8 Concluding Remarks

Time preference is attracting increased attention in microeconomic development studies that employ RCTs. A recurring theme in this literature is that individuals may lack self-control and patience and fail to take up profitable fertilizers (Duflo et al., 2011), fail to save (Ashraf et al., 2006), procrastinate at work (Kaur et al., 2015), or engage in excessive alcohol consumption (Schilbach, 2015). While such micro studies point to a nexus between patience and individual outcomes, little has been known about the broader macro implications of heterogeneity in time preference.

This paper has provided the first systematic investigation of the relationship between patience, accumulation behavior, and income on a global scale. Through a combination of reduced-form and simulation exercises, we have documented two key patterns. First, across levels of aggregation, patience is systematically linked to the accumulation of human capital, physical capital, the stock of knowledge, and income in a manner that is qualitatively consistent with micro- and macroeconomic theories of intertemporal choice. Second, the data reveal strong aggregation effects with respect to patience, and our back-of-the-envelope calibration suggests that the difference in magnitude of coefficients across levels of aggregation is roughly consistent with the general equilibrium effects in a parameterized version of our model.

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. A potential criticism of our work is that patience is potentially endogenous to

[11] To generate a test-retest correlation close to 0.6, a would have to be approximately 0.75 in size. However, with $a = 0.75$, 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.

institutions or education. While our empirical analysis has attempted to address such concerns, it is also worth noting that even if institutions or education were the ultimate drivers of all results in this paper, they 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 manifest in very old linguistic features (Chen, 2013), as well as historical agricultural productivity and crop yield (Galor and Özak, 2016). Future research might be able to disentangle the causal mechanisms 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).

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APPENDIX

A Details on Data Collection and Patience Measure

The description of the dataset builds on Falk et al. (forthcoming).

A.1 Overview

The cross-country dataset including risk aversion, patience, positive and negative reciprocity, altruism, and trust, was collected through the professional infrastructure of the Gallup World Poll 2012. The data collection process essentially consisted of three steps. First, we conducted an experimental validation procedure to select the survey items. Second, Gallup conducted a pre-test in a variety of countries to ensure the implementability of our items in a culturally diverse sample. Third, the final data set was collected through the regular professional framework of the World Poll 2012.

A.2 Experimental Validation

To ensure the behavioral relevance of our preference measures, all underlying survey items were selected through an experimental validation procedure. To this end, a sample of 409 German undergraduates completed standard state-of-the-art financially incentivized laboratory experiments designed to measure risk aversion, patience, positive and negative reciprocity, altruism, and trust. The same sample of subjects then completed a large battery of potential survey items. In a final step, for each preference, those survey items were selected which jointly performed best in predicting the behavior under real incentives measured in choice experiments. See Falk et al. (forthcoming) for details.

A.3 Pre-Test

Prior to including the preference module in the Gallup World Poll 2012, it was tested in the field as part of the World Poll 2012 pre-test, which was conducted at the end of 2011 in 22 countries. The main goal of the pre-test was to receive feedback and comments on each item from various cultural backgrounds in order to assess potential difficulties in understanding and differences in the respondents' interpretation of items. Based on respondents' feedback and suggestions, minor modifications were made to the wordings of some items before running the survey as part of the World Poll 2012.

The pre-test was run in 10 countries in central Asia (Armenia, Azerbaijan, Belarus, Georgia, Kazakhstan, Kyrgyzstan, Russia, Tajikistan, Turkmenistan, and Uzbekistan), 2 countries in South-East Asia (Bangladesh and Cambodia), 5 countries in Southern and Eastern Europe (Croatia, Hungary, Poland, Romania, Turkey), 4 countries in the Middle East and North Africa (Algeria, Lebanon, Jordan, and Saudi-Arabia), and 1 country in Eastern Africa (Kenya). In each country, the sample size was 10 to 15 people. Overall, more than 220 interviews were conducted. In most countries, the sample was mixed in terms of gender, age, educational background, and area of residence (urban / rural).

Participants in the pre-test were asked to state any difficulties in understanding the items and to rephrase the meaning of items in their own words. If they encountered difficulties in understanding or interpreting items, respondents were asked to make suggestions on how to modify the wording of the item in order to attain the desired meaning.

Overall, the understanding of both the qualitative items and the quantitative items was good. In particular, no interviewer received any complaints regarding difficulties in assessing the quantitative questions. When asked for rephrasing the qualitative patience item in their own words, most participants seemed to have understood the item in exactly the way that was intended.

However, when being confronted with hypothetical choices between monetary amounts today versus larger amounts one year later, some participants, especially in countries with current or relatively recent phases of volatile and high inflation rates, stated that their answer would depend on the rate of inflation, or said that they would always take the immediate payment due to uncertainty with respect to future inflation. Therefore, we decided to adjust the wording, relative to the "original" experimentally validated item, by adding the phrase "Please assume there is no inflation, i.e., future prices are the same as today's prices" to each question involving hypothetical choices between immediate and future monetary amounts.

A.4 Selection of Countries

Our goal when selecting countries was to ensure representativeness for the global population. Thus, we chose countries from each continent and each region within continents. In addition, we aimed at maximizing variation with respect to observables, such as GDP per capita, language, historical and political characteristics, or geographical location and climatic conditions. Accordingly, we favored non-neighboring and culturally dissimilar countries. This procedure resulted in the following sample of 76 countries:
East Asia and Pacific: Australia, Cambodia, China, Indonesia, Japan, Philippines, South Korea, Thailand, Vietnam

Europe and Central Asia: Austria, Bosnia and Herzegovina, Croatia, Czech Republic, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Italy, Kazakhstan, Lithuania, Moldova, Netherlands, Poland, Portugal, Romania, Russia, Serbia, Spain, Sweden, Switzerland, Turkey, Ukraine, United Kingdom
Latin America and Caribbean: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Guatemala, Haiti, Mexico, Nicaragua, Peru, Suriname, Venezuela
Middle East and North Africa: Algeria, Egypt, Iran, Iraq, Israel, Jordan, Morocco, Saudi Arabia, United Arab Emirates
North America: United States, Canada
South Asia: Afghanistan, Bangladesh, India, Pakistan, Sri Lanka
Sub-Saharan Africa: Botswana, Cameroon, Ghana, Kenya, Malawi, Nigeria, Rwanda, South Africa, Tanzania, Uganda, Zimbabwe

A.5 Sampling and Survey Implementation

A.5.1 Background

Since 2005, the international polling company Gallup has conducted an annual World Poll, in which it surveys representative population samples in almost every country around the world on, e.g., economic, social, political, and environmental issues. The collection of our preference data was embedded into the regular World Poll 2012 and hence made use of the pre-existing polling infrastructure of one of the largest professional polling institutes in the world.[12]

A.5.2 Survey Mode

Interviews were conducted via telephone and face-to-face. Gallup uses telephone surveys in countries where there is telephone coverage of at least 80% of the population or where this is the customary survey methodology. In countries where telephone interviewing is employed, Gallup uses a random-digit-dial method or a nationally representative list of phone numbers. In countries where face-to-face interviews are conducted, households are randomly selected in an area-frame-design.

A.5.3 Sample Composition

In most countries, samples are nationally representative of the resident population aged 15 and older. Gallup's sampling process is as follows.

[12]Compare http://www.gallup.com/strategicconsulting/156923/worldwide-research-methodology.aspx

Selecting Primary Sampling Units

In countries where face-to-face interviews are conducted, the first stage of sampling is the identification of primary sampling units (PSUs), consisting of clusters of households. PSUs are stratified by population size and / or geography and clustering is achieved through one or more stages of sampling. Where population information is available, sample selection is based on probabilities proportional to population size. If population information is not available, Gallup uses simple random sampling.

In countries where telephone interviews are conducted, Gallup uses a random-digit-dialing method or a nationally representative list of phone numbers. In countries where mobile phone penetration is high, Gallup uses a dual sampling frame.

Selecting Households and Respondents

Gallup uses random route procedures to select sampled households. Unless an outright refusal to participate occurs, interviewers make up to three attempts to survey the sampled household. To increase the probability of contact and completion, interviewers make attempts at different times of the day, and when possible, on different days. If the interviewer cannot obtain an interview at the initially sampled household, he or she uses a simple substitution method.

In face-to-face and telephone methodologies, random respondent selection is achieved by using either the latest birthday or else the Kish grid method.[13] In a few Middle East and Asian countries, gender-matched interviewing is required, and probability sampling with quotas is implemented during the final stage of selection. Gallup implements quality control procedures to validate the selection of correct samples and that the correct person is randomly selected in each household.

Sampling Weights

Ex post, data weighting is used to ensure a nationally representative sample for each country and is intended to be used for calculations within a country. First, base sampling weights are constructed to account for geographic oversamples, household size, and other selection probabilities. Second, post-stratification weights are constructed. Population statistics are used to weight the data by gender, age, and, where reliable data are available, education or socioeconomic status.

[13] The latest birthday method means that the person living in the household whose birthday among all persons in the household was the most recent (and who is older than 15) is selected for interviewing. With the Kish grid method, the interviewer selects the participants within a household by using a table of random numbers. The interviewer will determine which random number to use by looking at, e.g., how many households he or she has contacted so far (e.g., household no. 8) and how many people live in the household (e.g., 3 people, aged 17, 34, and 36). For instance, if the corresponding number in the table is 7, he or she will interview the person aged 17.

A.5.4 Translation of Items

The preference module items were translated into the major languages of each target country. The translation process involved three steps. As a first step, a translator suggested an English, Spanish or French version of a German item, depending on the region. A second translator, being proficient in both the target language and in English, French, or Spanish, then translated the item into the target language. Finally, a third translator would review the item in the target language and translate it back into the original language. If semantic differences between the original item and the back-translated item occurred, the process was adjusted and repeated until all translators agreed on a final version.

A.5.5 Adjustment of Monetary Amounts in Quantitative Items

All items involving monetary amounts were adjusted to each country in terms of their real value, i.e., all monetary amounts were calculated to represent the same share of the country's median income in local currency as the share of the amount in Euro of the German median income since the validation study had been conducted in Germany. Monetary amounts used in the validation study with the German sample were round numbers in order to facilitate easy calculations and to allow for easy comparisons (e.g., 100 Euro today versus 107.50 in 12 months). In order to proceed in a similar way in all countries, we rounded all monetary amounts to the next "round" number. While this necessarily resulted in some (very minor) variation in the real stake size between countries, it minimized cross-country differences in understanding the quantitative items due to difficulties in assessing the involved monetary amounts.

A.5.6 Staircase procedure

The sequence of survey questions that form the basis for the quantitative patience measure is given by the "tree" logic depicted in Figure 4 for the benchmark of the German questionnaire. Each respondent faced five interdependent choices between receiving 100 euros today or varying amounts of money in 12 months. The values in the tree denote the amounts of money to be received in 12 months. The rightmost level of the tree (5th decision) contains 16 distinct monetary amounts, so that responses can be classified into 32 categories which are ordered in the sense that the (visually) lowest path / endpoint indicates the highest level of patience. As in the experimental validation procedure in Falk et al. (2015), we assign values 1-32 to these endpoints, with 32 denoting the highest level of patience.

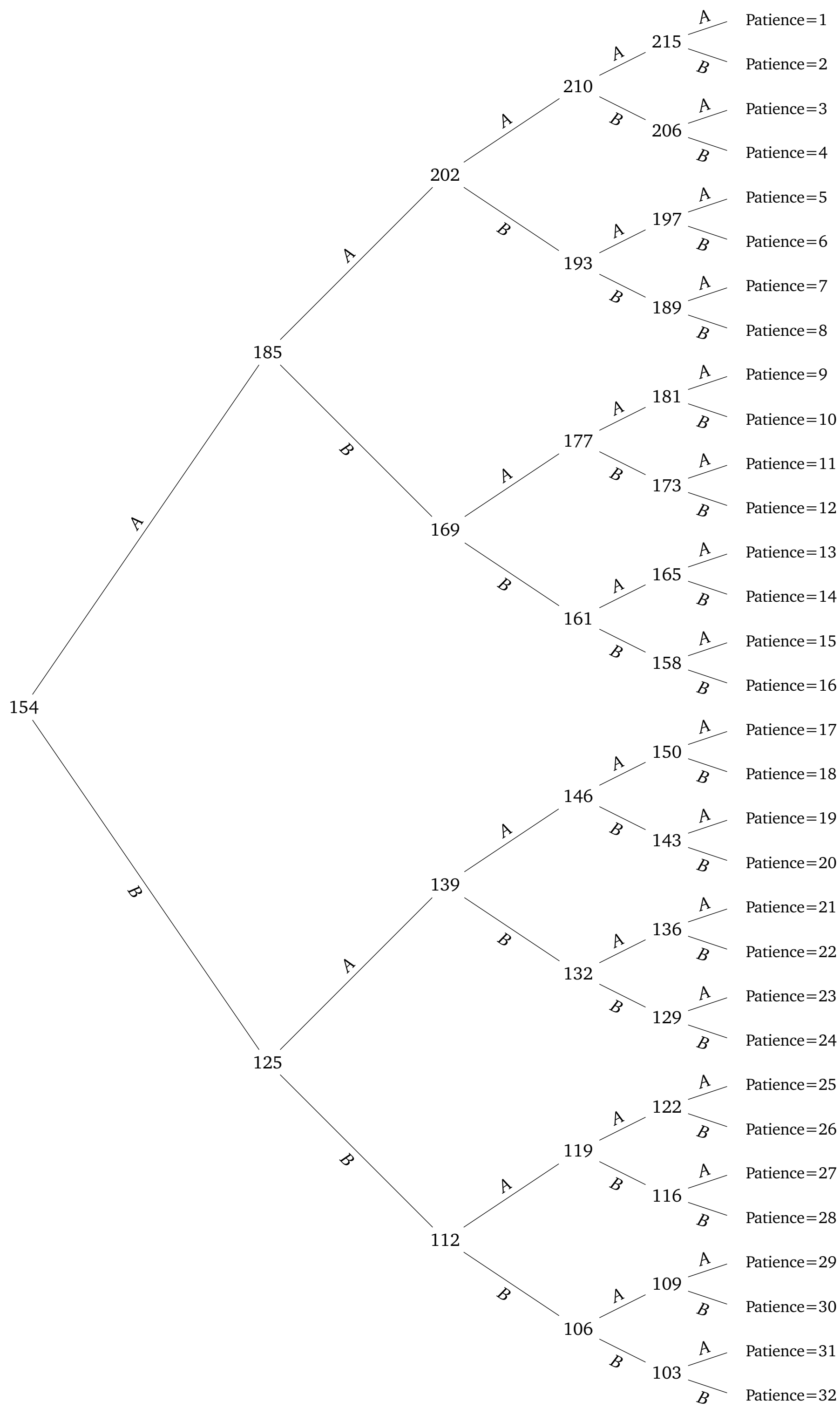

Figure 4: Tree for the staircase time task as implemented in Germany (numbers = payment in 12 months, A = choice of "100 euros today", B = choice of "x euros in 12 months"). First, each respondent was asked whether they would prefer to receive 100 euros today or 154 euros in 12 months from now (leftmost decision node). In case the respondent opted for the payment today ("A"), in the second question the payment in 12 months was adjusted upwards to 185 euros. If, on the other hand, the respondent chose the payment in 12 months, the corresponding payment was adjusted down to 125 euros. Working further through the tree follows the same logic.

A.6 Computation of Preference Measures

A.6.1 Cleaning and Imputation of Missings

In order to make maximal use of the available information in our data, missing survey items were imputed based on the following procedure:

If one survey item was missing, then the missing item was predicted using the responses to the other item. The procedure was as follows:

- Qualitative question missing: We regress all available survey responses to the qualitative question on responses to the staircase task, and then use these coefficients to predict the missing qualitative items using the available staircase items.
- Staircase item missing: The imputation procedure was similar, but made additional use of the informational content of the responses of participants who started but did not finish the sequence of the five questions. If the respondent did not even start the staircase procedure, then imputation was done by predicting the staircase measure based on answers to the qualitative survey measure using the methodology described above. On the other hand, if the respondent answered at least one of the staircase questions, the final staircase outcome was based on the predicted path through the staircase procedure. Suppose the respondent answered four items such that his final staircase outcome would have to be either x or y. We then predict the expected choice between x and y based on a probit of the "x vs. y" decision on the qualitative item. If the respondent answered three (or less) questions, the same procedure was applied, the only difference being that in this case the obtained predicted probabilities were applied to the expected values of the staircase outcome conditional on reaching the respective node. Put differently, the procedure outlined above was applied recursively by working backwards through the "tree" logic of the staircase procedure.

In total, for about 8% of all respondents, one of the two patience measures was imputed.

A.6.2 Computation of Preference Indices at Individual Level

We compute an individual-level index of patience by (i) computing the z-scores of each survey item at the individual level and (ii) weighing these z-scores using the weights resulting from the experimental validation procedure of Falk et al. (forthcoming). Formally, these weights are given by the coefficients of an OLS regression of observed behavior on responses to the respective survey items, such that the coefficients sum to one. These weights are given by (see above for the precise survey items):

$$\text{Patience } = 0.7115185 \times \text{ Quantitative measure } + 0.2884815 \times \text{ Qualitative item}$$

A.6.3 Computation of Country Averages

In order to compute country-level averages, we weigh the individual-level data with the sampling weights provided by Gallup, see above.

B Model Derivations and Quantification

B.1 Patience, Factor Accumulation, and Growth: A Simple Model

Setup. Consider an economy of overlapping generations of individuals that live for two 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 choose the fractions of labor earnings they want to consume and save. 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 youth fully depreciates at the end of their second period of life. During youth, individuals also decide about their education. In terms of education, individuals can decide to remain unskilled workers or to become educated workers during the second period of their life. Becoming educated requires individuals to spend fraction $(1-\psi)$ of their time on the acquisition of human capital.

Let generations be indexed by the period when they are young. Then the preferences of individual i are represented by

$$U^i = \ln c_t^y + \beta^i \ln c_{t+1}^o \,, \tag{1}$$

where β^i is the discount factor of individual i, which corresponds to this individual's level of patience.[14] Individuals differ in their patience, and for analytical convenience β^i is modeled as a draw from a uniform distribution $\beta^i \sim U[\chi-\epsilon;\chi+\epsilon]$ with density $1/2\epsilon$, where χ reflects the average level of patience in a given country.[15] Variation in β^i conditional on χ captures individual-level heterogeneity within an economy. Variation in χ will be used below to conduct comparisons between populations.

Human Capital Acquisition. The acquisition of education takes a fraction $1-\psi$ of the first period of life. We assume that the effectiveness of time spent on education increases with patience, so that an individual with patience β^i accumulates a stock of human capital $h(\beta^i) = \beta^i e^{\rho(1-\psi)}$, which corresponds to the usual Mincerian specification with education time $(1-\psi)$ and a return parameter $\rho > 0$. Technically, the assumption that the effectiveness of time devoted to education increases with patience, serves the

[14]For notational clarity, in the following we denote a cohort by the period in which this generation is young.

[15]The assumption of a uniform distribution of patience is made for analytical tractability and simplicity. Any realistic parametric distribution would deliver qualitatively similar results.

purpose to break the well-known separation theorem.[16]

Budget Constraints. Denote the wage of unskilled workers by w_t^W, the earnings of an educated entrepreneurial worker as w_t^E, the savings rates of unskilled and educated workers as s_t^W and s_t^E, and the return on capital as R_t. The respective budget constraints of unskilled and educated workers are then

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

$$\text{educated:} \quad c_t^y = w_t^W \cdot (1 - s_t^{iE}) \cdot \psi, \qquad c_{t+1}^o = w_{t+1}^E \cdot h_t(i) + w_t^W \cdot s_t^{iE} \cdot \psi \cdot R_{t+1} \tag{3}$$

Individuals take wages and capital returns as given.

Production. Output can be used for consumption or capital accumulation, and is produced using capital, unskilled labor and educated labor. The production of final output Y during period t takes the form

$$Y_t = A_t K_t^\alpha \left[L_t^{\frac{\sigma-1}{\sigma}} + H_t^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma(1-\alpha)}{\sigma-1}}, \tag{4}$$

where the aggregate capital stock in period t is K_t, the stock of unskilled labor in t is denoted by L_t, and the effective stock of educated labor is H_t, with $0 < \alpha < 1$ and $\sigma > 1$. Factors are remunerated on competitive markets for capital, and for unskilled and educated labor, respectively, such that

$$R_t = \alpha A_t K_t^{\alpha-1} \left[L_t^{\frac{\sigma-1}{\sigma}} + H_t^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma(1-\alpha)}{\sigma-1}} \tag{5}$$

$$w_t^W = (1-\alpha) A_t K_t^\alpha \left[L_t^{\frac{\sigma-1}{\sigma}} + H_t^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma(1-\alpha)}{\sigma-1}-1} L_t^{-1/\sigma} \tag{6}$$

$$w_t^E = (1-\alpha) A_t K_t^\alpha \left[L_t^{\frac{\sigma-1}{\sigma}} + H_t^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma(1-\alpha)}{\sigma-1}-1} H_t^{-1/\sigma} \tag{7}$$

In its basic form, the model does not feature any feedback of patience on factor productivity or or growth in terms of technological progress. However, the model can easily be extended to accommodate both features by making the additional assumption of a human capital externality of the stock of educated workers on productivity or productivity growth. In particular, we apply a simplified version of a human capital

[16]Otherwise, in an environment as the one described here, where savings allow to smooth consumption, education choices do not interfere with intertemporal trade-offs and only maximize lifetime income. This assumption therefore essentially parallels the assumption of incomplete capital markets in models without savings and physical capital, see, e.g., Doepke and Zilibotti (2014) and Klasing and Milionis (2014). Under a broad class of alternative modeling assumptions, human capital accumulation and occupation choice will also depend on patience.

externality on productivity (e.g., Lucas, 1988) for TFP, with $A_t = \bar{A} \cdot (1 + H_t)^{\theta}$, and a mechanism along the lines of Nelson and Phelps (1966) according to which larger share of educated workers in the population is conducive for productivity growth,

$$g_t = \frac{A_{t+1} - A_t}{A_t} = \lambda_t^{\phi} \tag{7}$$

where $\phi > 0$. For most of the analysis, we will abstract from TFP externalities and growth, i.e., set $\theta = \phi = 0$.

In the following, we restrict attention to the steady state (balanced growth) equilibrium.

Optimal Individual Decisions. The model is closed by considering the optimal decisions at the individual level. The optimal savings decision for an unskilled worker is determined by maximizing (1) subject to (2).

In steady state the optimal savings rate of an unskilled worker i are given by

$$s^{iW}(\beta^i) = \frac{\beta^i - \frac{(1+g)}{R}}{1 + \beta^i}, \tag{8}$$

which is strictly increasing in individual i's patience β^i.

Analogously, the optimal savings decision for individual i conditional on becoming an educated worker is determined by maximizing (1) subject to (3). Solving for the optimal savings rate in the steady state gives

$$s^{iE}(\beta^i) = \frac{\beta^i - \frac{(1+g)\eta h(\beta^i)}{R\psi}}{1 + \beta^i}, \tag{9}$$

where $\eta = w^E/w^W$ denotes the skill premium of educated workers as defined in the main text.

It turns out that educated entrepreneurs can afford to save a smaller fraction of their first period income than unskilled workers in order to smooth consumption.[17]

The choice to become an unskilled worker or an educated worker involves a comparison of (indirect) lifetime utilities. After cancelling common terms (wages), this com-

[17] This logic corresponds to comparing the second period labor incomes for unskilled workers and skilled workers while holding β^i fixed. While young, workers earn the same wages regardless of whether they become skilled or remain unskilled. When becoming skilled, however, the disposable income during youth is lower due to the time spent on education, $(1-\psi)$. This implies that the savings rate of workers that become skilled is lower than of those that remain unskilled, conditional on the same β^i, as becomes clear from a comparison of (9) and (8) and noting that $0 < \psi < 1$ and $\eta > 1$.

parison can be represented as

$$\ln(1-s^{iW})+\beta^i\ln((1+g)+s^{iW}R)\gtrless\ln\left((1-s^{iE})\psi\right)+\beta^i\ln\left((1+g)\eta h(\beta^i)+\psi s^{iE}R\right).$$

Substituting from the optimal savings decision and simplifying yields as equivalent condition

$$\frac{1-\psi}{1+g}R+1\gtrless\eta h(\beta^i)=\eta\beta^i e^{\rho(1-\psi)} \tag{10}$$

The right hand side of this condition, which corresponds to the relative marginal utility in the second period of becoming educated rather than unskilled, is increasing in patience β^i since a higher β^i implies a greater effectiveness of time devoted to education for individuals with greater patience. The indifference condition for becoming unskilled vs. educated is that $\tilde{\beta}=\left(\frac{1-\psi}{1+g}R+1\right)\frac{1}{\eta e^{\rho(1-\psi)}}$, with a strict preference for becoming educated if $\beta^i>\tilde{\beta}$.

Factor Market Clearing. In the following, we restrict attention to the steady state (balanced growth) equilibrium. In this environment, each generation will consist of a share $\lambda_t=\lambda$ of individuals that decide optimally to become educated. This share of individuals is characterized by a level of patience greater or equal than $\tilde{\beta}_t$. Since unskilled workers of two generations coexist at each point of time, the stock of unskilled labor in steady state is given by

$$L=\frac{1}{2\epsilon}\left(2\cdot\int_{\chi-\epsilon}^{\tilde{\beta}}1d\beta+\int_{\tilde{\beta}}^{\chi+\epsilon}\psi d\beta\right)=2(1-\lambda)+\psi\lambda\,. \tag{11}$$

Correspondingly, the stock of skilled workers in a given period is given by λ, and the aggregate stock of skilled human capital corresponds to

$$H=\frac{1}{2\epsilon}\int_{\tilde{\beta}}^{\chi+\epsilon}e^{\rho(1-\psi)}\beta d\beta=e^{\rho(1-\psi)}\lambda(\chi+\epsilon-\lambda\epsilon)\,, \tag{12}$$

where $\tilde{\beta}$ corresponds to the threshold level patience that determines the stock of skilled workers.

Equilibrium. The indifference condition for education implies the existence of a threshold level of patience, $\tilde{\beta}$. In equilibrium, the marginal individual with patience $\tilde{\beta}$ is indifferent between remaining an unskilled worker or becoming educated. Individuals with a $\beta^i>\tilde{\beta}$ optimally sort into becoming educated, whereas individuals with $\beta^i<\tilde{\beta}$

decide to remain unskilled workers. For any non-degenerate distribution of β, there is a one-to-one mapping between $\tilde{\beta}$ and the respective population share of skilled individuals λ_t.

Under the assumption that β^i is distributed uniformly, this mapping is $\lambda = (\chi + \epsilon - \tilde{\beta})/2\epsilon \Leftrightarrow \tilde{\beta} = \chi + \epsilon - 2\lambda\epsilon$. Consequently, the average level of patience of unskilled workers is then given by $\underline{\beta} = \chi - \lambda\epsilon$. Equivalently, the average patience of educated workers is $\bar{\beta} = \chi + (1-\lambda)\epsilon$.

The wage premium of educated workers over unskilled workers is therefore

$$\eta = \frac{w^E}{w^W} = \left(\frac{L}{H}\right)^{\frac{1}{\sigma}} = \left(\frac{2(1-\lambda)+\psi\lambda}{e^{\rho(1-\psi)}\lambda(\chi+\epsilon-\lambda\epsilon)}\right)^{\frac{1}{\sigma}}, \tag{13}$$

and is strictly decreasing in λ.

Notice that wage earnings when young correspond to unskilled wages and are therefore unrelated to individual patience, so that aggregate savings are obtained by occupation-specific averages. The (interior) steady state equilibrium is therefore characterized by a partition of the population in unskilled workers and educated workers, as well as the corresponding supply and demand of capital. To determine the equilibrium, notice that imposing equality of the indifference condition for remaining unskilled or acquiring skills, (10) and simplifying delivers a condition for the effective return to capital R, which itself is a function of the population share skilled λ, i.e., the share of the population with a patience greater than $\tilde{\beta}$,

$$R = \frac{1+g}{1-\psi}\left(\eta h(\tilde{\beta}) - 1\right) \tag{14}$$

which is strictly decreasing in λ.

Next, consider the supply of capital. Since the capital stock depreciates after one period (generation), the capital stock in one period is given by the total savings of the young generation during the previous period. On the balanced growth path, this implies that the supply of capital is given by

$$K = \frac{w^W}{2\epsilon}\left(\int_{\chi-\epsilon}^{\tilde{\beta}} s^{iW}(\beta)d\beta + \psi\int_{\tilde{\beta}}^{\chi+\epsilon} s^{iE}(\beta)d\beta\right) \tag{15}$$

Substituting the respective conditions for optimal savings choices and simplifying delivers

$$
\begin{aligned}
K^{1-\alpha} \quad = \quad & \frac{A}{2\epsilon}(1-\alpha)K^{\alpha}\left[L^{\frac{\sigma-1}{\sigma}}+H^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma(1-\alpha)}{\sigma-1}-1}L^{-1/\sigma}\cdot \qquad (16)\\
& \left\{\left[(\tilde{\beta}-(\chi-\epsilon))-\left(1+\frac{1+g}{R}\right)\left(\ln(1+\tilde{\beta})-\ln(1+(\chi-\epsilon))\right)\right]\right.\\
& \left.+\left[\psi\left(1-\frac{(1+g)\eta e^{(1-\psi)\rho}}{\psi R}\right)\left((\chi+\epsilon-\tilde{\beta})-(\ln(1+\chi+\epsilon)-\ln(1+\tilde{\beta}))\right)\right]\right\}
\end{aligned}
$$

as expression for capital supply.

The inverse demand for capital is given by $R = \alpha A K^{\alpha-1}\left[L^{\frac{\sigma-1}{\sigma}}+H^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma(1-\alpha)}{\sigma-1}}$. Rearranging delivers

$$
K^{1-\alpha}=\frac{\alpha A}{R}\left[L^{\frac{\sigma-1}{\sigma}}+H^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma(1-\alpha)}{\sigma-1}}. \qquad (17)
$$

Equalizing the expressions for capital supply and capital demand and simplifying yields the following implicit function of λ that determines the equilibrium split of the population into unskilled workers and educated entrepreneurs,

$$
\begin{aligned}
1 \quad = \quad & \frac{1-\alpha}{\alpha}\frac{1}{2\epsilon}\frac{R}{(2(1-\lambda)+\lambda\psi)^{(}1/\sigma)}\cdot \qquad (18)\\
& \left\{\left[(\tilde{\beta}-(\chi-\epsilon))-\left(1+\frac{1+g}{R}\right)\left(\ln(1+\tilde{\beta})-\ln(1+(\chi-\epsilon))\right)\right]\right.\\
& \left.+\left[\psi\left(1-\frac{(1+g)\eta e^{(1-\psi)\rho}}{\psi R}\right)\left((\chi+\epsilon-\tilde{\beta})-(\ln(1+\chi+\epsilon)-\ln(1+\tilde{\beta}))\right)\right]\right\}.
\end{aligned}
$$

Eliminating R by making use of the equilibrium condition for the equilibrium fractions of unskilled and skilled workers, (14), and substituting η gives the same condition only in terms of λ and parameters.

The λ that solves this condition pins down the equilibrium fraction of unskilled workers and educated workers, thereby determining the scope of production in terms of the effective levels of labor supply of both types of workers and of capital that are consistent with firm optimization and optimal individual savings and education choices in steady state. In general, the equilibrium λ depends on parameters $\{\alpha, \sigma, \psi, \rho\}$ as well as the distribution parameters χ and ϵ. There exists a unique $0 < \lambda \leq 1$ that solves this equation.[18]

[18]For the proof of existence, notice that the right hand side of (17) exhibits a vertical asymptote at $e^{\rho(1-\psi)}\eta\tilde{\beta} = 1$ due to $R = 0$ as in (14). A sufficient condition for existence is that the expression before the braces on the right hand side of (17) is infinite at $\lambda = 0$. This is the case since $R(0 \leftarrow \lambda) \rightarrow \infty$ as $\eta(0 \leftarrow \lambda) \rightarrow \infty$. The existence of an interior equilibrium is then established by applying the intermediate value theorem. To establish uniqueness, notice that the expression before the braces on the right hand

B.2 The Effect of Variation in Patience on Factor Accumulation and Income

Variation in Patience Across Individuals. To gauge the effect of patience on factor accumulation and incomes, we begin by considering comparative statics at the individual level, keeping the aggregate allocation unchanged. Technically, this implies conducting comparative statics with respect to β^i, conditional on a given distribution of β, in particular a given χ.

The statement that more patient individuals save more and consume less of their earnings during the first period of their life is obtained by noticing that savings of both types of workers are increasing in β.[19] Moreover, compare the share of income consumed of two individuals with $\underline{\beta} < \bar{\beta}$. Considering unskilled workers, from (8) it can be seen that the more patient individual consumes less and saves more, $\frac{1-s^W(\bar{\beta})}{1-s^W(\underline{\beta})} = \frac{1+\underline{\beta}}{1+\bar{\beta}} < 1$. The same holds for individuals that become educated, applying the same logic to (9).

The higher propensity to acquire human capital for individuals with a higher β^i follows directly from (10).

Regarding the effect of patience on individual income, notice first that with a fixed allocation there is essentially no individual return to patience for unskilled workers, since their income is unaffected by savings, which only serve to smooth consumption. Unskilled workers adjust their savings primarily depending on the trade-off between patience and capital returns.[20] At the same time, more patient individuals are more likely to become skilled because this affords them strictly higher lifetime incomes as consequence of the labor income from skilled workers' wages during the second period of their lives.[21] The marginal effect of higher patience on average individual income is therefore positive.

Taken together this discussion implies the testable predictions that, on average, the effect of patience on savings, education and income is positive on the individual level, as stated in the main text.

side of (17) is strictly monotonically decreasing in λ. The expression inside the braces is also strictly monotonically decreasing in λ such that, due to the chain rule, the entire right hand side is strictly monotonically decreasing in λ.

[19]For unskilled workers, this follows directly from (8). For educated workers, this can be ensured by imposing the parametric restriction $\frac{\psi}{1-\psi}\psi(\chi-\epsilon) - \frac{\psi}{(1+g)} > e^{\rho(1-\psi)}$.

[20]Lifetime income for the average unskilled worker with patience $\bar{\beta}^W$ is given by income from worker wages in both periods of life as well as the capital income during the second period of life, $y^W = w^W\left(2+s^W(\bar{\beta}^W)R\right)$. The individual return to patience is therefore $\frac{\partial y^W}{\partial \bar{\beta}^W} = w^W R \frac{\partial s^W(\bar{\beta}^W)}{\partial \bar{\beta}^W} = w^W \tilde{R} \frac{1+\frac{(1+g)}{\tilde{R}}}{(1+\bar{\beta}^W)^2} > 0$.

[21]The income of a the average educated worker is the wage as unskilled worker during young ages net of education time, plus the income as educated worker in old age, $y^E = w^W\left(1+(1+g)\eta(\bar{\beta}^S)+\psi s^E(\bar{\beta}^E)R\right)$. The average return to patience for an individual educated workers is therefore positive since η and s^E are increasing in $\bar{\beta}$.

Variation in Patience Across Populations. The considerations at the individual level neglect the effect of variation of patience at the aggregate level. To see the additional implications, consider two regions or countries that differ in terms of the distribution of patience of their populations. To be concrete, consider two countries that differ only with respect to χ, where the country with a higher χ represents a society that is more future oriented, i.e., more patient overall, while the heterogeneity (in terms of the uniform distribution and ϵ) is the same across both countries. Hence, the patience distribution of the more future oriented country is stochastically dominated (the distribution is shifted to the right). As a consequence, given the human capital production function, output is larger for the economy with a higher χ when keeping the worker composition in terms of λ and savings fixed. In addition, the steady state skill composition differs across the two countries. In particular, the steady state share of skilled workers is unambiguously higher in the country with a more patient population.[22] The shift in patience in combination with a greater equilibrium λ implies an unambiguously larger stock of skilled labor H, a lower stock of unskilled labor L, as well as a lower skill premium. Together with a sufficiently high return to education ρ, the composite labor stock is larger in total. Finally, aggregate savings are unambiguously larger, such that from (17) the interest rate R is lower. Hence, under these conditions, greater average patience implies an unambiguously greater aggregate income.

B.3 Model Quantification

General procedure. To illustrate the quantitative implications of the model, we calibrate the model presented in Section 2 for two countries which only differ in their average patience, i.e., we compare the 10th and the 90th percentile of the cross-country distribution of (average) patience. This procedure has the attractive feature that the patience difference between these two countries equals almost exactly one standard deviation, which means that our results can be compared with the OLS regressions in which the patience variable was normalized to have mean zero and standard deviation of one. In the simulations, we will evaluate the effect of varying patience by one standard deviation at both the individual and the country level to gauge whether the difference in effect sizes is in the ballpark of the results established in the correlational analyses.

[22]From the uniqueness proof, the right hand side of (17) is known to be decreasing in λ. In addition, the right hand side of (17) is increasing in χ since R is increasing in χ. Moreover, a sufficient (but not necessary) condition for the term in braces (aggregate savings) to be increasing in χ is that $\chi + \epsilon < \frac{1-\psi}{1+\psi}$. Under these conditions, the result then follows from applying the implicit function theorem.

Patience parameters. Parameterizing the model requires data on χ (the country mean of patience) as well as ϵ (which equals half the support of the uniform distribution of patience values). Our reduced-form estimations make use of a composite patience measure that does not lend itself to a quantitative interpretation in terms of β. For the purposes of the calibration, we hence resort to the quantitative "staircase" procedure only. When responding to this item, respondents went through a series of five binary choices between immediate and delayed monetary rewards. This procedure in principle allows us to pin down (a range of) β for each respondent. However, as is well-known in the behavioral economics literature, discount factors that are naïvely extrapolated from experimental or survey data tend to be much smaller than the discount factors that are typically used in macro calibration exercises. One of the key reasons for this is the lack of information about the respondents' wealth level. The typical implicit assumption behind the extrapolation is that respondents do not integrate their decision with their wealth. This, however, mechanically leads to unrealistically low implied discount factors.[23]

In order to obtain a realistic mapping between decisions in our quantitative survey procedure and χ, we re-calibrate the quantitative interpretation of the empirical patience measure by making an explicit assumption about the (uniform) level of wealth respondents have in mind when making their decisions. Specifically, we pin down β by computing the wealth level that – if plugged into expected utility maximization with CRRA utility and $\gamma = 1$ – generates annual $\beta = 0.96$ at the 10th percentile of the cross-country distribution of patience.[24] We then compute annual β at the 90th percentile based on this wealth level, which equals 0.975. The model requires that these annual patience values be expressed for 25 years, which equals one generation. Hence, $\chi_l \approx 0.37$ and $\chi_h \approx 0.57$. Finally, we assume $\epsilon = 0.3$ so that the calibrated total standard deviation equals the difference in the means of patience across countries.[25]

Parameter Choices. Calibrating the model requires assumptions about the following parameters: $1 - \psi$ (the time cost of becoming skilled), α (the capital income share), σ (the elasticity of substitution between skilled and unskilled labor), and ρ (the scaling parameter reflecting the effectiveness of patience for skilled entrepreneurial labor). Regarding the time cost, we assume $\psi = 0.76$, which corresponds to education costs

[23]Additional problems in estimating discount rates from oberved choices are heterogeneous utility curvature and expectations-based loss aversion.

[24]This wealth level is equivalent to 270 euros. Obviously, this wealth level is not to be taken literally. Recall that much experimental work has shown that people indeed *do* tend to neglect their lifetime wealth when making experimental choices, so that 270 euros should heuristically be thought of as wealth level weighted by the propensity to narrow bracket experimental decisions.

[25]This also takes into account measurement error in the patience variable.

equivalent to six years (and hence roughly the length of advanced secondary and tertiary education or a vocational degree) if "young age" in our model lasts from age 15 to 40. We further assume a capital income share of $\alpha = 0.4$, which approximately corresponds to recent estimates by the IMF (World Economic Outlook, April 2017). Consistent with the usual estimate reported in the literature, we assume $\sigma = 1.4$ (Acemoglu and Autor, 2011). Finally, we set $\rho = 2$, which implies a return to a year of skilled education of approximately 12% in the present framework, which is in the range of what is considered reasonable in the literature (see, e.g., Caselli, 2017).[26] In the baseline simulation, we abstract from growth. In the extensions with human capital externalities on TFP and TFP growth, we set $\theta = 0.3$, which is conservative given the estimates of Thönnessen and Gundlach (2013), and $\phi = 0.61$ following Cervellati and Sunde (2015).

[26]The de facto return depends on the range of β-parameters. This parameter determines the range for interior solutions for λ and governs the growth rate along the balanced growth path, consistent with using the average return as empirical counterpart.

C Details for Regional-Level Analysis

Our regional-level data contain 704 regions (typically states or provinces) from the following countries: Argentina (16), Australia (8), Austria (9), Bolivia (8), Brazil (24), Cambodia (14), Cameroon (10), Canada (10), Chile (12), China (23), Colombia (23), Czech Republic (7), Egypt (3), Germany (16), Finland (4), France (22), Georgia (10), Ghana (10), Great Britain (12), Greece (13), Hungary (7), India (24), Indonesia (17), Iran (30), Israel (6), Italy (17), Jordan (6), Kazakhstan (6), Kenya (8), Lithuania (10), Macedonia (3), Malawi (3), Mexico (28), Morocco (13), Nigeria (6), Nicaragua (17), Netherlands (12), Pakistan (4), Poland (16), Portugal (7), Romania (8), Russia (27), Serbia (2), Spain (19), Sri Lanka (9), Sweden (8), Tanzania (20), Thailand (5), Turkey (4), Uganda (4), Ukraine (27), United Arab Emirates (7), USA (51), South Africa (9), Zimbabwe (10)

D Aggregation Effects

The main text has shown that the coefficient on patience becomes successively larger as one moves to higher levels of aggregation. This Appendix discusses two mechanical reasons that might drive this pattern, i.e., measurement error and resulting attenuation bias and censoring of the patience variable.

D.1 Measurement Error

If individual-level patience is measured with noise, then our country-level average patience measure will be a less noisy estimate of true country-level patience than our individual-level patience estimate. This difference in measurement error would lead to stronger attenuation at subnational levels and hence generate differences in coefficient magnitudes across levels of aggregation.

While we do not question that our data are affected by measurement error, this section investigates how large this measurement error would have to be to generate the observed differences in coefficients. To this end, we generate a synthetic patience measure for which we know the true relationship between income and patience at all levels of aggregation. We then subject this synthetic measure to noise and investigate how much noise we need to inflict on the synthetic measure to generate differences in coefficient sizes across aggregation levels that mirror those observed in our data. To this end, we focus on the comparison between (i) an OLS regression of log household income on patience, conditional on country fixed effects, and (ii) an OLS regression of log GDP p/c on average patience at the country level. Specifically, we conduct the following exercise:

1. To gauge the magnitude of amplification between individual-level and country-level regressions, we develop the following benchmark:

    - Regress household income on patience and country fixed effects.
    - Compute average household income (as proxy for GDP p/c) and average patience by country. Regress average household income on average patience.
    - Compute the ratio of patience coefficients in these two regressions. In our data, this ratio equals 39.

2. Generate a synthetic "true" patience measure which equals log household (respondent) income per capita. By construction, this "true" patience variable has a coefficient of one both when regressing household income on individual patience, and when regression average household income (as proxy for GDP p/c) on average patience.

3. From this "true" patience, we generate a synthetic "observed" patience variable, which equals $p_o = p_t + \alpha \times \epsilon$, where β_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 mean zero and standard deviation of one, so the noise term has the same magnitude as patience).

4. We regress household income on this "observed" patience variable. We also aggregate household income and "observed" patience at the country level and regress average household income on average "observed" patience. We then scale α so that the ratio of observed coefficients equals 39 as in our actual data. It turns out that this requires $\alpha \approx 6$.

5. We evaluate whether $\alpha = 6$ is reasonable. To do so, we generate two separate synthetic "observed" patience variables from the same underlying synthetic "true" patience (this can be thought of as eliciting patience from the same respondent twice). For each individual, we take $\alpha = 6$ and the noise terms ϵ are independent across individuals and "observed" patience variables. The correlation between these two synthetic "observed" patience variables (conditional on country fixed effects) is $\rho = 0.02$.

Given that experimental studies report test-retest correlations for preferences in the ballpark of 0.6 (Beauchamp et al., 2011), we conclude that $\alpha = 6$ is much too large to be meaningful. Indeed, to generate a correlation of 0.6 between the two synthetic "observed" patience measures, we would need to assume $\alpha = 0.75$. But with such a low α, the ratio of coefficients across levels of aggregation equals just 1.7, which is much lower than the observed ratio of 39.

D.2 Censoring

The patience variable is subject to left-censoring because we can only estimate an upper bound on patience for those respondents who always opt for the immediate payment in the quantitative staircase task. This left-censoring can lead to expansion bias. If such expansion bias was stronger at the country level than at the individual level, this could drive the observed pattern of coefficient magnitudes.

To check whether this is the case, we conduct two separate exercises. The first one is very similar to the thought experiment regarding measurement error above: we generate a synthetic patience measure, censor the measure and then investigate how this effects the OLS coefficients at the individual and country level:

1. Generate a synthetic "true" patience measure which equals log household (respondent) income per capita. By construction, this "true" patience variable has a coefficient of one both when regressing household income on individual patience, and when regression average household income (as proxy for GDP p/c) on average patience.

2. From this "true" patience, we generate a synthetic "observed" patience variable, which is censored: we replace all patience values below the median with the median "true" patience.

3. We regress household income on this "observed" patience variable. We also aggregate household income and "observed" patience at the country level and regress average household income on average "observed" patience. The ratio of observed coefficients equals 1.4, much lower than in the actual data.

As a second – conceptually different – exercise, we remove all censored individuals from the sample and then re-run the OLS regressions of (i) household income on patience, conditional on country fixed effects, and (ii) of average household income on average patience. If censoring drove the difference in coefficients, then this exercise might considerably reduce the coefficient ratio. However, in these regressions, the ratio of patience coefficients is 41, i.e., almost exactly identical to the coefficient ratio when we employ the full sample of respondents. We conclude from these two exercises that censoring is unlikely to drive the amplified patience coefficient at higher levels of aggregation.

E Additional Tables

Table 12: Patience and national income: Additional control variables

	Dependent variable: Log [GDP p/c PPP]					
	(1)	(2)	(3)	(4)	(5)	(6)
Patience	2.00***	1.92***	1.70***	1.23**	1.26**	1.31**
	(0.30)	(0.33)	(0.37)	(0.51)	(0.56)	(0.56)
Trust	-0.097	0.064	-0.37	-0.42	-0.59	-0.75
	(0.39)	(0.35)	(0.42)	(0.47)	(0.55)	(0.61)
Risk taking	-0.78**	-0.58	-0.40	-0.67*	-0.53	-0.64
	(0.33)	(0.35)	(0.33)	(0.39)	(0.45)	(0.47)
Mean elevation		-0.92*	-1.42***	-0.95**	-1.10*	-1.07
		(0.52)	(0.44)	(0.45)	(0.63)	(0.72)
Standard deviation of elevation		-0.43	0.068	0.075	0.20	0.22
		(0.49)	(0.40)	(0.32)	(0.39)	(0.41)
Terrain roughness		3.10***	2.20**	0.43	1.04	0.73
		(1.04)	(1.00)	(1.38)	(2.08)	(2.12)
Mean distance to nearest waterway		-0.57**	-0.87***	-0.97***	-0.85**	-0.88**
		(0.28)	(0.30)	(0.32)	(0.32)	(0.35)
1 if landlocked		0.37	0.63*	0.54	0.43	0.47
		(0.33)	(0.33)	(0.38)	(0.35)	(0.40)
Log [Area]		0.15	0.19*	0.16	0.14	0.14
		(0.11)	(0.11)	(0.11)	(0.11)	(0.12)
Linguistic fractionalization			0.18	0.52	0.22	0.41
			(0.38)	(0.45)	(0.56)	(0.57)
Religious fractionalization			-0.51	-0.94**	-0.93	-0.64
			(0.46)	(0.46)	(0.59)	(0.65)
Ethnic fractionalization				-0.29	0.0034	-0.10
				(0.68)	(0.70)	(0.65)
% of European descent						0.053
						(0.60)
Genetic distance to the U.S. (weighted)						0.016
						(0.07)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
Legal origin FE	No	No	No	Yes	Yes	Yes
Major religion shares	No	No	No	No	Yes	Yes
Observations	74	74	72	72	72	71
R^2	0.86	0.88	0.90	0.92	0.94	0.94

OLS estimates, robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Major religion shares include the share of Protestants, Catholics, Muslims, Buddhists, Hinduists, and Atheists. See column (4) of Table 1 for a complete list of the additional controls.

Table 13: Patience and national income in sub-samples

	Dependent variable: Log [GDP p/c PPP] in...							
	Africa & Middle East	Europe & C. Asia	SE Asia & Pacific	Americas	OECD	Non-OECD	Colonized	Not colonized
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patience	2.49***	1.55***	3.28***	2.16***	1.03***	1.32**	2.18***	2.00***
	(0.70)	(0.24)	(0.96)	(0.34)	(0.16)	(0.56)	(0.32)	(0.46)
Observations	20	27	14	15	22	54	54	22
R^2	0.28	0.48	0.40	0.53	0.62	0.07	0.30	0.46

OLS estimates, robust standard errors in parentheses. In the first column, the sample includes Africa and the Middle East, in the second column Europe and Central Asia, in the third South-East Asia and Pacific, in the fourth the Americas, in the fifth (sixth) all (non-) OECD members, and the seventh (eigth) all formerly colonized (never colonized) countries. The regional groups follow the World Bank definitions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

F Description and Sources of Main Variables

F.1 Country-Level Outcome Variables

GDP per capita. Most recent available data point starting at 2016. Source: World Bank Development Indicators.

Annual growth rates. Computed from Maddison dataset.

Average years of schooling. Barro and Lee (2012), data in 2010 for population aged 25 and over.

Enrolment rates. Barro and Lee (2012), year 2010.

Cognitive skills. Measure of cognitive skills derived from a series of standardized tests in math, science, and reading across countries, see Hanushek and Woessmann (2012).

Education expenditure. Most recent available data point starting at 2016. Source: World Bank Development Indicators.

Capital stock. Data taken from the Penn World Tables.

National savings. Gross savings are calculated as gross national income less total consumption, plus net transfers. Net national savings are equal to gross national savings less the value of consumption of fixed capital. Adjusted net savings are equal to net national savings plus education expenditure and minus energy depletion, mineral depletion, net forest depletion, and carbon dioxide and particulate emissions damage. Most recent available data point starting at 2016. Source: World Bank Development Indicators.

Household savings rate. The household saving rate is calculated as the ratio of household saving to household disposable income (plus the change in net equity of households in pension funds). Source: QOG database.

Total factor productivity. TFP level at current PPPs (USA=1), taken from QOG dataset.

R&D expenditure. Expenditures for research and development are current and capital expenditures (both public and private) on creative work undertaken systematically to increase knowledge, including knowledge of humanity, culture, and society, and the use of knowledge for new applications. R&D covers basic research, applied research, and experimental development. Most recent available data point starting at 2016. Source: World Bank Development Indicators.

Number of researchers in R&D. Researchers in R&D are professionals engaged in the conception or creation of new knowledge, products, processes, methods, or systems and in the management of the projects concerned. Most recent available data point starting at 2016. Source: World Bank Development Indicators.

Democracy index. Index that quanties the extent of institutionalized democracy, as reported in the Polity IV dataset. Taken from QOG dataset.

Property rights. This factor scores the degree to which a country's laws protect private property rights and the degree to which its government enforces those laws. It also accounts for the possibility that private property will be expropriated. In addition, it analyzes the independence of the judiciary, the existence of corruption within the judiciary, and the ability of individuals and businesses to enforce contracts. Average 2003-2012, taken from the QOG dataset.

Oil production per capita. Oil production per capita in 2014 Dollars. Taken from Quality of Government dataset.

F.2 Regional-Level Data

Except for the patience measures and a region's size (area), all regional-level data are taken from Gennaioli et al. (2013). The area data were collected by research assistants from various sources on the web.

F.3 Individual-Level Data

Household income per capita. Included in Gallup's background data. To calculate income, respondents are asked to report their household income in local currency. Those respondents who have difficulty answering the question are presented a set of ranges in local currency and are asked which group they fall into. Income variables are created by converting local currency to International Dollars (ID) using purchasing power parity (PPP) ratios. Log household income is computed as log (1+ household income).

Education level. Included in Gallup's background data. Level 1: Completed elementary education or less (up to 8 years of basic education). Level 2: Secondary - 3 year tertiary education and some education beyond secondary education (9-15 years of education). Level 3: Completed four years of education beyond high school and / or received a 4-year college degree.

Subjective self-assessment of math skills. Included in Gallup's background data. *How well do the following statements describe you as a person? Please indicate your answer on a scale from 0 to 10. A 0 means "does not describe me at all" and a 10 means "describes me perfectly". You can also use any numbers between 0 and 10 to indicate where you fall on the scale, like 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10. I am good at math.*

Saved last year. Binary variable capturing whether the respondent saved any money in the previous year. Included in Gallup's background data.

Confidence in financial institutions. Included in Gallup's background data. Binary response to the question "In this country, do you have confidence in each of the following, or not? How about financial institutions or banks?"

Subjective institutional quality. Included in Gallup's background data. This variable consists of a perceived institutional quality index as it is provided by Gallup. This index combines binary questions (yes / no) about whether people have confidence in the military, the judicial system and courts, the national government, and the honesty of elections. The index is then constructed by averaging the yes / no answers across items.

Subjective law and order index. Included in Gallup's Background data. Derived from responses to three questions: "In the city or area where you live, do you have confidence in the local police force?"; "Do you feel safe walking alone at night in the city or area where you live?"; "Within the last 12 months, have you had money or property stolen from you or another household member?".