All Over the Map
A Worldwide Comparison of Risk Preferences*

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Abstract

We obtain rich measurements of risk preferences for 2939 subjects across 30 countries, and use the data to paint a picture of the distribution of risk preferences across the globe using structural equation models. Reference-dependence and likelihood-dependence are found to be important everywhere. Model parameters in non-Western countries differ systematically from those in Western countries, with poorer countries substantially more risk tolerant than rich countries on average. We qualify previous findings on gender effects and cognitive ability by showing how they mainly impact likelihood-dependence. We further add novel evidence on the correlation between risk preferences and study major. Whereas we confirm previous results on observable characteristics of subjects explaining little of overall preference heterogeneity, a few macroeconomic indicators can explain a considerable part of the between-country heterogeneity.

Keywords: risk preferences; cultural comparison; prospect theory

JEL-classification: C93; D03; D80; O12

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1 Motivation

Risk preferences have long been known to be too complex to be described by a single parameter (Vickrey, 1945; Friedman and Savage, 1948). Instead, the degree of risk tolerance of decision makers has been found to vary systematically with prospect characteristics. Reference-dependence leads to differences in preferences for gains and losses relative to a reference point. It also results in loss aversion, the empirical finding that a given loss is attributed considerably more weight than an equivalent gain (Markowitz, 1952). Likelihood-dependence constitutes a departure from expected utility theory (EU) whereby probabilities are not weighted linearly, but are subjectively distorted (Preston and Baratta, 1948; Abdellaoui, Baillon, Placido and Wakker, 2011). Both reference-dependence and likelihood-dependence are integrated into prospect theory (PT; Tversky and Kahneman, 1992), and have been shown to be crucial to account for e.g. insurance uptake (Barseghyan, Molinari, O'Donoghue and Teitelbaum, 2013) and behavior in financial markets (Odean, 1998; Barberis, 2013).

In a provocative article, Henrich, Heine and Norenzayan (2010) showed that many findings in the social sciences that had been thought of as 'established' did not fare well once exposed to a rigorous test across different cultures. We present comparative results on risk preferences from 30 countries including close to 3,000 subjects obtained in controlled, incentivized experiments. We obtain rich measurements for each subject, allowing us to estimate a flexible version of prospect theory—a crucial element in an exploratory comparative analysis. What is more, for two-outcome prospects as used in our experiment, nearly all existing non-EU theories are special cases of PT (Wakker, 2010, section 7.11). Such theories include original prospect theory (Kahneman and Tversky, 1979), rank-dependent utility (Quiggin, 1982), and disappointment aversion (Gul, 1991).

We elicit risk preferences using certainty equivalents (CEs). Participants choose between a lottery or *prospect* with fixed characteristics and a changing sure amount contained between the extreme outcomes of the prospect. This serves to avoid the formation of endogenous references points (Hershey and Schoemaker, 1985; Vieider, 2017), and thus allows us to fix the reference point to zero. Together with their simplicity, this feature has made CEs the prime tool to elicit PT parameters (Tversky and Kahneman, 1992; Bruhin, Fehr-Duda and Epper, 2010; Abdellaoui et al., 2011). By changing prospect characteristics across choice lists, we are able to introduce the orthogonality in the characteristics of the choice problems necessary to identify the parameters of a multi-dimensional theory such as PT. Instead of using the single choices from each choice list, we then estimate the parameters by directly comparing the elicited CEs to a theoretically derived CE following Bruhin et al. (2010).

The data reveal both commonalities and differences across countries. We find risk tolerance to decrease in the probability of winning a prize in every country for gains (with reflected, albeit somewhat less regular, patterns for losses). This shows the universality of likelihood-insensitivity. We also find reference-dependence and loss aversion in all countries. The main difference consists in subjects in less developed countries exhibiting higher levels of risk tolerance on average for both gains and losses. This casts doubt on 'strong' interpretations of prospect theory, which incorporate typical parameter values in addition to the mathematical framework of the theory (e.g., an inverse-S shaped probability weighting function crossing the 45° line at about 1/3 for both gains and losses).

Building on von Gaudecker, van Soest and Wengström (2011), we show that adopting a more flexible model does not change the conclusion that little of the individual-level variance is explained by observable characteristics. At the same time, we do find stable correlates of our model parameters. We qualify the effects of well-known correlates of risk preferences such as gender and physical height (Dohmen, Falk, Huffman, Sunde, Schupp and Wagner, 2011; Filippin and Crosetto, 2015), by showing that they mostly correlate with likelihood-dependence rather than with overall levels of risk tolerance. The same holds true for the effect of cognitive ability, adding to the debate on the effect of cognitive ability on risk tolerance (Benjamin, Brown and Shapiro, 2013; Andersson, Tyran, Wengström and Holm, 2016). We also present new insights into the effect of study characteristics on risk preferences (which—somewhat ironically given the heavy reliance on student samples in the discipline—have not been systematically documented to date). Finally, we can explain a large part of the between-country variance using a few macroeconomic characteristics.

Our research is related to a number of other papers. Bruhin et al. (2010) estimated a finite mixture model for Chinese and Swiss students, finding similar proportions of subjects deviating from EU. Rieger, Wang and Hens (2015) presented survey data on risk preferences obtained from hypothetical lottery choices with economics students across 53 countries. An even larger data set, comprising risk preferences as well as intertemporal and social preferences, has recently been presented by Falk, Becker, Dohmen, Enke, Huffman and Sunde (2015). While containing data from representative samples in a large number of countries, that data set relies on a single hypothetical measure capturing risk taking behavior. Our data are much richer at the individual level, allowing for the estimation of structural models. The two approaches are thus complementary.

The data of Rieger et al. (2015), on the other hand, present at least two major problems. First, the authors elicit willingness-to-pay for gains, and willingness-to-accept for losses. This turns all observations into mixed prospects (Kahneman, Knetsch and Thaler, 1991a; Bateman, Kahneman, Munro, Starmer and Sugden, 2005). The difference in framing between gains and losses also distorts comparisons between them. Second, their stimuli are not sufficiently rich to allow for a full estimation of PT parameters. Whereas Rieger, Wang and Hens (2017) report an estimation of PT, they are forced to assume a one-parameter probability weighting function and to restrict this parameter to be equal for gains and losses. Such restrictive assumptions are difficult to reconcile with the purpose of capturing between-country differences in preferences, and we will show that both a two-parameter weighting function and different parameters for gains and losses are needed to properly account for our data.

This paper proceeds as follows. Section 2 introduces the theoretical setup and empirical strategy. Section 3 describes the subject pool and the experimental procedures. Section 5 presents results on the main correlates of risk preferences. Section 6 introduces heterogeneity across unobservable characteristics. Section 7 discusses the results and concludes the paper.

2 Theoretical setup

We model preferences using prospect theory (Tversky and Kahneman, 1992). Let $(x, p; y)$ be a binary prospect, where p represents the probability of winning or losing x, and y obtains with a complementary probability $1-p$, $|x| > |y|$. We describe choices between such binary prospects and sure amounts of money. Under PT, utility is generated over changes in wealth rather than over total wealth as under EU, incorporating the intuition that people adapt their reference points to their current situations (Markowitz, 1952). Preferences are thus reference-dependent, i.e. they may differ for gains and losses relative to a reference point. The experiment was framed in such a way that the reference point corresponds to zero (Tversky and Kahneman, 1992; Bruhin et al., 2010; Abdellaoui et al., 2011). For outcomes that fall purely into one domain, i.e. $x > y \geq 0$ or $0 \geq y > x$, we can represent the utility of a prospect, PU, as follows:

$$PU = w^s(p)v(x) + (1 - w^s(p))\, v(y), \tag{1}$$

where the probability weighting function, $w(p)$, is a continuous and strictly increasing function that satisfies $w(0) = 0$ and $w(1) = 1$; the superscript s indicates sign-dependence and can take the values $+$ for gains and $-$ for losses; and $v(.)$ represents a utility function which indicates preferences over outcomes. Under PT, utility curvature cannot be automatically equated with risk preferences, since the latter are determined jointly by the utility and the weighting functions (Schmidt and Zank, 2008). For mixed prospects, where $x > 0 > y$, the utility of the prospect can be represented as:

$$PU = w^+(p)v(x) + w^-(1 - p)v(y). \tag{2}$$

In order to specify the model set out above, we need to determine the functional forms to be used. Whereas PT is very flexible, it has the disadvantage that the utility and weighting functions can exhibit a substantial degree of collinearity when using parametric estimations in the presence of noise (Zeisberger, Vrecko and Langer, 2012). This issue becomes particularly bothersome when estimations are based on relatively few observations, which is the case when we estimate parameter distributions over all subjects in our random parameter model. In our favorite specification, we thus assume utility to be piecewise linear:

$$v(x) = \begin{cases} x & \text{if } x > 0 \\ -\lambda(-x) & \text{if } x \leq 0 \end{cases} \tag{3}$$

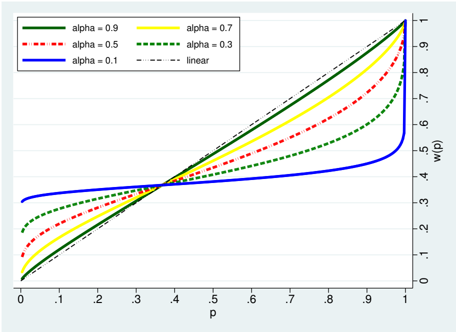
where $\lambda > 1$ indicates loss aversion, captured by a kink in the utility function at the origin (Köbberling and Wakker, 2005; Abdellaoui, Bleichrodt and Paraschiv, 2007). Loss aversion is a central component of risk aversion, and has been indicated as the main driver of small stakes risk aversion (Rabin, 2000; Rabin and Thaler, 2001), the willingness-to-pay willingness-to-accept disparity (Bateman et al., 2005), the endowment effect (Kahneman, Knetsch and Thaler, 1991b), and the equity premium puzzle (Benartzi and Thaler, 1995). Risk preferences are thus completely captured by probability weighting and loss aversion. While this may appear unusual to economists, it captures a fundamental psychological intuition about risk preferences. In the words of Yaari (1987), "at the level of fundamental principles, risk aversion and diminishing marginal utility of wealth ... are horses of different colors. The former expresses an attitude towards risk (increasing uncertainty hurts), whereas the latter expresses an attitude towards wealth (the loss of a sheep hurts more when an agent is poor than when an agent is rich)" (p. 95). While utility curvature is clearly important when stakes are large, allowing for non-linear utility generally only takes up some of the risk preferences otherwise captured in probability weighting over the relatively modest stake ranges we use (see Bouchouicha and Vieider, 2017a, for specific evidence on stake variation under PT). This simplification further provides a good compromise between descriptive fit and tractability. In particular, it fits the aggregate data better than alternative simplifications, such as EU ($z = 60.45, p < 0.001$; Vuong ,1989, test; all results are stable to using a Clark test instead), or reference-depend models assuming linear probabilities and non-linear utility ($z = 44.68, p < 0.001$; Markowitz, 1952; von Gaudecker et al., 2011). A robustness check abandoning this assumption is included in the Online Appendix.

For probability weighting, we adopt the 2-parameter weighting function proposed by Prelec (1998). Using an alternative two-parameter function by Goldstein and Einhorn (1987) does not qualitatively affect our results. We used the function developed by Prelec as it provides a significantly better fit to our aggregate data ($z = 3.606, p < 0.001$, Vuong test):

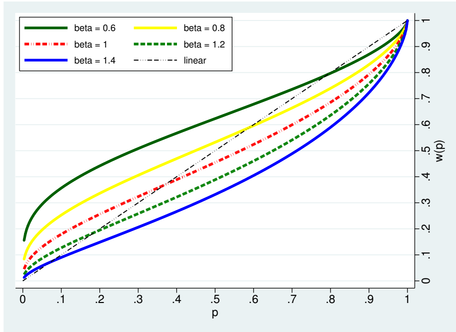
$$w^s(p) = exp(-\beta^s(-ln(p))^{\alpha^s}), \tag{4}$$

where s again indicates gains and losses. The parameter α governs the curvature of the probability weighting function, with $\alpha = 1$ indicating that probabilities are treated linearly (the EU case), and $\alpha < 1$ representing the typical case of likelihood-insensitivity. This results in the characteristic inverse S-shaped weighting function (Wu and Gonzalez, 1996; Abdellaoui, 2000; Bleichrodt and Pinto, 2000; Kilka and Weber, 2001). Likelihood-insensitivity captures the phenomenon whereby a given change in probability is attributed a greater weight when it is added to a probability of 0 or subtracted from a probability of 1 than in the intermediate probability range. It can account for many important empirical observations, the prime example amongst which is the coexistence of insurance and lottery play (Friedman and Savage, 1948; Markowitz, 1952; Kahneman and Tversky, 1979). The effect of changes in α for a fixed value of $\beta = 1$ are illustrated in figure 1(a). Holding β constant, a decrease in α will indicate more extreme risk preferences at the probability endpoints (providing it was 1 or smaller to start with), and less sensitivity to changes in probabilities in the middle of the probability spectrum. We will henceforth refer to α simply as *sensitivity*.

The parameter β determines where an inverse S-shaped function will cross the 45 degree line. This is illustrated in figure 1(b) for the case of $\alpha = 0.65$. For $\beta = 1$, the function will cross at $^1/_e$. This crossing point shifts to the left



(a) Changes in α for $\beta = 1$



(b) Changes in β for $\alpha = 0.65$

Figure 1: Illustration of weighting parameters

and downwards for values of β larger than 1, and to the right and upwards for values smaller than 1. Holding α constant, larger values of β will thus indicate a decrease in risk tolerance for gains, and an increase in risk tolerance for losses under our linear utility assumption. We will henceforth refer to the β parameter as *pessimism* for gains, and as *optimism* for losses.

3 Experimental setup and methods

The experiment was conducted in 30 countries distributed across all inhabited continents. The countries were chosen according to the economic importance, geographical location, and to obtain diversity across dimensions such as GDP per capita and the Hofstede (1980) cultural attitudes scales. We used in particular the Hofstede scales in guiding our selection of countries in regions that might otherwise seem relatively homogenous, such as Europe. Indeed, whereas European or Latin American countries may share a general cultural heritage and similar levels of economic development, they differ markedly on some of the Hofstede scales, such as in respect to their uncertainty avoidance. Students were used in order to obtain high quality data, and because the use of homogenous population pools is generally considered desirable in international comparisons (Hofstede, 1980). Potential issues arising from selection effects will be discussed below.

The data this paper is based on were first introduced by Vieider, Lefebvre, Bouchouicha, Chmura, Hakimov, Krawczyk and Martinsson (2015a). That paper did, however, not provide a detailed analysis of the risk preference data across prospects, using only non-parametric measures of risk preferences aggregated across probabilities and stake levels, and focusing on correlations with survey questions devised to capture risk taking behavior, as well as with aggregate measures for uncertainty (unknown probabilities). This is thus the main paper on risk preferences in the comparative dataset. A companion paper on ambiguity attitudes uses stimuli included in the experiment for which no precise probabilities were provided, and the analysis of which is not included in this paper (L'Haridon, Vieider, Aycinena, Bandur, Belianin, Cingl, Kothiyal and Martinsson, 2017).

A total of 2939 subjects took part in the experiment. Subjects were generally recruited at major public universities located in the capital or in other major cities of a country. Exceptions to this rule were Brazil, Malaysia, Saudi Arabia, and Tunisia, where we conducted the experiment at a private university (see Appendix for the exact location of the experiments). We made every effort to keep conditions as similar as possible across countries. We recruited subjects using flyers, which announced economic experiments in which subjects could earn money according to their choices. Amounts to be won were not mentioned. In countries where we could recruit through standing subject pools, we only recruited subjects who were relatively new to experiments (< 3) in order to keep conditions as equal as possible across countries. We tried to recruit subjects with an eye to equal gender proportions and to a wide representation of study majors. This did not always work to the desired point—in Saudi Arabia, for instance, our male contact was not allowed to interact with female students, so that we have an all male sample. An overview of the main subject characteristics can be found in appendix A. The complete instructions are included in the Online Appendix (for languages other than English, see www.ferdinandvieider.com/instructions.html).

A total of 28 prospects are included in this study. In addition, 16 more prospect were included in the experiment to measure ambiguity, and are not discussed here. Prospects were kept in a fixed order so as to make the task easier to understand. Since the experiment was conducted using paper and pencil, this made the organization more straightforward, and avoided potential issues deriving from different order proportions in different countries. A large-scale pilot with 330 subjects in Vietnam showed that preferences elicited in such a fixed order were no different from those elicited in a randomized order, while resulting in lower noise levels (results available upon request). Gains were always presented first. There were 14 prospects for risky gains and 13 prospects for risky losses, plus one mixed prospect to determine loss aversion (one prospect being enough to identify loss aversion, given that all other parameters are identified from pure gains or pure losses). For both gains and losses, we presented prospects with 50-50 probabilities first, namely $\{5, 0; 10, 0; 20, 0; 30, 0; 30, 10; 30, 20\}$ and $\{-5, 0; -10, 0; -20, 0; -20, -5; -20, -10\}$. These prospects were followed by prospects in order of ascending probability, with $p = i/8, i = 1, ..., 8$, offering either the PPP-equivalent of €20 or 0 (-20 or 0 for losses), as well as 20 or 5 (-20 or -5) with the two extreme probabilities. Losses were always implemented from an endowment equal to the maximum possible loss, given conditional on the loss part being selected for payoff determination.

In order to guarantee comparability across countries, we converted the payoffs using purchasing power parity (PPP). All experiments were run between September 2011 and October 2012. The duration of the experiment was about one hour, and the expected payoff for an expected value maximizer was about €18, including a show-up fee of €4. We used PPP data from the World Bank for 2010 as our main conversion tool. In addition, we checked the conversion rates using net hourly wages of student assistants at the university where the experiments were carried out. Adjustments based on the wage rates mainly aided us in rounding decisions. One may be worried that differences between countries may nonetheless be influenced by imprecisions in PPP conversions. Pilots showed that stake variations in the range of $\pm 20\%$ did not impact estimated risk preferences (Vieider, 2012). Another issue in international comparisons is that the 'treatment' of interest is given by the socio-cultural and socio-economic background of subjects, for which randomization is clearly impossible. To ensure that differences were not simply driven by selection effects, in another pilot Vieider, Chmura, Fisher, Kusakawa, Martinsson, Mattison Thompson and Sunday (2015b) examined the differences in preferences obtained at various locations within a country. Almost no within-country differences in risk preferences were found once observable characteristics of decision makers were controlled for. Potential selection effects deriving from using only students will be further discussed below, based on results obtained with general population samples.

For each prospect, subjects faced a choice between sure amounts varying in equal steps between the minimum and maximum amount in the prospect, and the prospect itself (with exception of the mixed prospect). The sure amount always covered the whole range of the prospect, to avoid issues deriving from cutting off choice lists arbitrarily (Andersson et al., 2016). The certainty equivalent of the prospect was the midpoint between the two points where preference switched. This was meant to exclude the possibility of obtaining rates of multiple switching that differed between countries, and to have to exclude such subjects, since imputing a preference satisfying monotonicity to multiple switchers would require additional assumptions. At the end of the game, one of the choices for which a decision had to be made between a prospect and a sure amount was randomly selected for real pay—the standard procedure in the literature (Cubitt, Starmer and Sugden, 1998; Abdellaoui et al., 2011).

4 Econometric model

Identification

The choice lists included in our experiment were designed explicitly in such a way as to allow us to separately identify the PT parameters introduced above, which jointly describe the risk preferences of decision makers. While nonparametric methods to measure the different PT components exist (Wakker and Deneffe, 1996; Abdellaoui, 2000), such methods are typically more difficult to administer, and may suffer from error propagation because of their chained nature. Certainty equivalents, on the other hand, require structural estimations to elicit the full set of PT parameters. Under our linear utility assumption, which allows in principle for a non-parametric description of results, the fitting of functional forms permits us to reduce the number of parameters significantly, and thus to more efficiently summarize the results.

Let us begin from our favorite specification assuming piecewise linear utility. Probability weighting can be identified simply from variation in probabilities, while keeping outcomes constant. For gains or losses, we can write the indifference between the CE and the prospect simply as $ce = w(p)x + (1 - w(p))y$. By rearranging and solving the equation for $w(p)$, we obtain:

$$w(p) = \frac{ce - y}{x - y}. \tag{5}$$

This equation allows us to nonparametrically trace a probability weighting function from the prospects offering (the PPP equivalent of) €20 or else zero with different probabilities of winning the prize. The distance of the probability weights from the 45° line for the different probabilities p, given by $w(p) - p$, now serves to identify the pessimism/optimism parameter β. In particular, larger CEs in absolute terms result in more elevated functions, which *ceteris paribus* indicate increased optimism for gains (since the weight is attached to the best outcome) and increased pessimism for losses (since the weight is attached to to the worst outcome). At the same time, the sensitivity parameters α are determined by the way the distance $w(p) - p$ changes when probabilities change. In particular, the typical inverse-S shape of the probability weighting function results from a positive difference when probabilities are small, which turns into a negative difference as probabilities increase.

Once the probability weights have been identified, it is straightforward to identify loss aversion. The latter results from an indifference between a sure zero outcome and a prospect $(x, 0.5; y)$, which gives the identity $0 = w^+(0.5)x - \lambda w^-(0.5)y$. By rearranging, we obtain:

$$\lambda = \frac{w^+(0.5)x}{w^-(0.5)y}. \tag{6}$$

Since the probability weights are identified following equation 5, this directly identifies the loss aversion parameter λ. In particular, holding the ratio $^{w^+(0.5)}/_{w^-(0.5)}$ of probability weights constant, the smaller the absolute loss amount $|y|$ starting from which a respondent prefers playing the lottery over the status quo, the higher her level of loss aversion.

Finally, we briefly discuss the identification of the whole PT model, including nonlinear utility over gains and losses. Given that we now have an additional parameter describing risk preferences in the pure gain and pure loss domains, we can no longer recover the functions nonparametrically using CEs. The identification of the utility function then derives from varying the outcomes of a prospect while keeping the probabilities constant. For a given probability weighting function, any change in risk preferences must now be reflected in utility curvature. To be able to cleanly separate utility and probability weighting, it is furthermore essential to include nonzero lower outcomes in the prospect, which serves to avoid collinearity in the parameters which would make their separation impossible. Under deterministic choice, this serves to clearly separate utility from probability weighting. Issues may, however, occur in the presence of measurement noise—see Zeisberger et al. (2012) for simulation results and a detailed discussion.

Stochastic modelling and econometrics

For a given prospect involving pure gains or losses, we can represent the modeled certainty equivalent, $\hat{ce}_i$, under the assumption of deterministic choice as follows:

$$\hat{ce}_i = w^s(p_i)x_i + (1 - w^s(p_i))y_i \tag{7}$$

For mixed prospects with $x_i > 0 > y_i$, we can define the modeled equivalent loss $\hat{y}_i$ that makes the decision maker indifferent between the mixed prospect and the status quo:

$$\hat{y}_i = \frac{w^+(p_i)x_i}{\lambda w^-(1 - p_i)}. \tag{8}$$

Both the modeled certainty equivalents $\hat{ce}_i$ in Equation 7 and the modeled loss equivalents $\hat{y}_i$ in Equation 8 depend on the preference parameters $\{\alpha^s, \beta^s, \lambda\}$. The difference in the identifying equation is driven by the difference in elicitation methods for mixed prospects and for gains and losses.

We now introduce an explicit stochastic structure. We start from the observation that responses recorded in the experiment will be affected by noise, be it generated by errors in utility calculation, errors in recording the answers, or from the mis-specification of the model relative to the true underlying decision process generating the data (Train, 2009). The observed certainty equivalent ce_i will thus be equal to the certainty equivalent calculated from our model plus some independently distributed error term, or $ce_i = \hat{ce}_i + \epsilon_i$. We assume this error to be normally distributed, $\epsilon_i \sim \mathcal{N}(0, \sigma_i^2)$. The parameter σ_i indicates the standard deviation of a so-called Fechner error (Hey and Orme, 1994; Loomes and Sugden, 1995; Loomes, 2005).

We allow for three different types of heteroscedasticity following Bruhin, Fehr-Duda and Epper (2010). Firstly, the error is allowed to differ between gains and losses. We define the error parameter for losses as the sum of the error parameter for gains plus a domain-specific error component ω. For mixed prospects, we adopt the error for losses, since it is the loss amount that varies in the mixed choice lists. Secondly, we allow the error term to depend on the specific prospect, or rather, on the difference between the high and low outcome in the prospect, such that $\sigma_{si} = \sigma_s |x_i - y_i|$. For the mixed prospects, the error term depends on the maximum range in the loss domain. This takes into account that the error may be related to the length of the choice list, which will vary with the difference between the two outcomes of the prospect given fixed steps between the sure amounts. Finally, we let the error term σ depend linearly on the characteristics of the decision maker, n, so that $\sigma_s = \sigma_0 + X_n \eta$, with η a vector of regression parameters. This specification performs significantly better than a homoscedastic specification according to a likelihood ratio test ($\chi^2(1) = 14603.76, p < 0.001$).

We can express the probability density function $\psi(.)$ for a given subject n and prospect ξ_i as follows

$$\psi(\theta_n, \xi_i) = \phi\left(\frac{\hat{ce}_{ni}(\alpha_n^s, \beta_n^s, \lambda_n) - ce_{ni}}{\sigma_{nis}}\right) \tag{9}$$

where ϕ is the standard normal density function, and $\theta_n = \{\alpha_n^s, \beta_n^s, \lambda_n, \sigma_n, \omega\}$ indicates the vector of model parameters. The $s = +$ index is omitted from the parameter σ_n for notational convenience. For mixed prospects, $\hat{ce}_i$ and ce_i have to be replaced by $\hat{y}_i$ and y_i respectively in Equation (9).

The individual likelihood function is equal to the product of the density functions above across all prospects:

$$L_n(\theta_n) = \prod_i \psi(\theta_n, \xi_i). \tag{10}$$

Taking logs and summing over individuals, we obtain the following aggregate log-likelihood function:

$$LL(\theta_k, \gamma) = \sum_{n=1}^{N} \log\left[L_n(\theta_n)\right] \tag{11}$$

Within this grand likelihood, we let the vector of parameters depend linearly on the observable characteristics of decision makers, such that $\theta_n = \theta_k + X_n\gamma$, where θ_k is a vector of constants and X_n represents a matrix of observable characteristics of the decision maker. For simplicity, the parameter ω is assumed to be independent of the characteristics of the decision maker.

We use a random parameter model to take into account unobserved heterogeneity in addition to the observed heterogeneity captured by γ in the model above. This amounts to estimating the distribution of the parameters θ_n from the aggregate data. We make two assumptions here. First, we transform the parameters using an exponential function, thus imposing that all parameters be positive.[1] Second, we assume the parameter distributions based on unobservable characteristics to be normally distributed, independent of the observable characteristics, and independent of each other. This amounts to assuming that

[1]For example, the error term $sigma_n$ for a decision maker n is defined as $exp(\xi_{i,\sigma} + X_n\eta)$, for an individual effect $\xi_{i,\sigma}$ capturing unobserved heterogeneity.

ζ, the vector of random parameters, follows a multivariate normal distribution with mean zero and diagonal covariance matrix $\Omega = \Sigma\Sigma'$.[2] Conditional on a given realization of ζ, the contribution to the likelihood for subject n is given by Equation (10). The unconditional contribution to the likelihood for subject n is:

$$L_n(\theta_k, \gamma, \Sigma) = \int_{\mathbb{R}^6} \prod_i \zeta(\theta_n, \xi_i) f(\zeta|\Omega) d\zeta, \tag{12}$$

where $f(.)$ denotes the multivariate normal distribution, and the dimension of the integral corresponds to the number of parameters to be estimated. Taking logs and summing over individuals gives the aggregate log-likelihood function to be maximized.

We estimate the log-likelihood function (11) in Stata using standard estimation techniques, and use it to determine the effects of observable characteristics in sections 5.1 to 5.4. The errors are always clustered at the subject level. Because the multiple integral in Equation (12) does not have a closed-form solution, we estimate the log-likelihood function by maximum-simulated likelihood. The estimation is performed in Matlab using Halton sequences of length 500 per individual.[3] We use it to represent heterogeneity across unobservable characteristics in section 6. All estimations employ the BFGS algorithm.

5 Results

We present the results in four stages. We start by presenting aggregate estimates for our global data. We then move on to the between-country comparison. This involves showing differences between countries, as well as trying to determine possible factors explaining such differences. The third stage looks at individual-

[2]This specification does not allow for correlation accross individual-specific parameters, which is a limitation of our approach. This limitation is justified by computational reasons. Relaxing this hypothesis would require imposing additional assumptions (e.g identity of parameters between gains and losses, imposing a one-parameter form for the probability weighting function, or restricting the impact of observable heterogeneity) in order keep the number of estimated parameters reasonable.

[3]Morokoff and Caflisch (1995) shows that Halton sequences give the best performance in terms of integration error for multiple integrals with dimensions up to 6 (see also Train, 2009, on Halton sequences).

level correlates controlling for country fixed effects. Stage four then takes a look at overall heterogeneity and the extent to which the latter can be explained through individual and country characteristics.

5.1 Global estimates

We start by presenting the global estimates of our preference functions. This establishes a benchmark of 'globally representative preference parameters', albeit for students only. The probability weighting functions for gains and losses are shown in figure 2. For both gains and losses, we find considerable likelihood-insensitivity, with $\alpha^+ = 0.602$ ($se = 0.005$) and $\alpha^- = 0.641$ ($se = 0.006$). In terms of pessimism for gains and optimism for losses, we find $\beta^+ = 0.908$ ($se = 0.003$) and $\beta^- = 0.941$ ($se = 0.004$). Although the parameters are significantly different between gains and losses from a statistical point of view, the two functions can be seen to be economically very similar. This is an indication of *reflection* at this highest level of aggregation, resulting in risk seeking for small probability gains and large probability losses, and in risk aversion for small probability losses and large probability gains. We furthermore find clear evidence for loss aversion, with $\lambda = 1.939$ ($se = 0.017$) being close to, but slightly below, the often-cited benchmark value of 2.

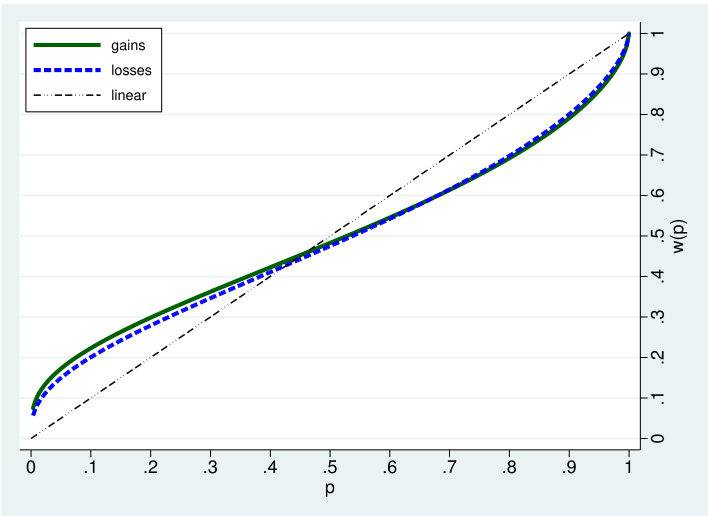


Figure 2: Probability weighting functions for gains and losses based on the global data

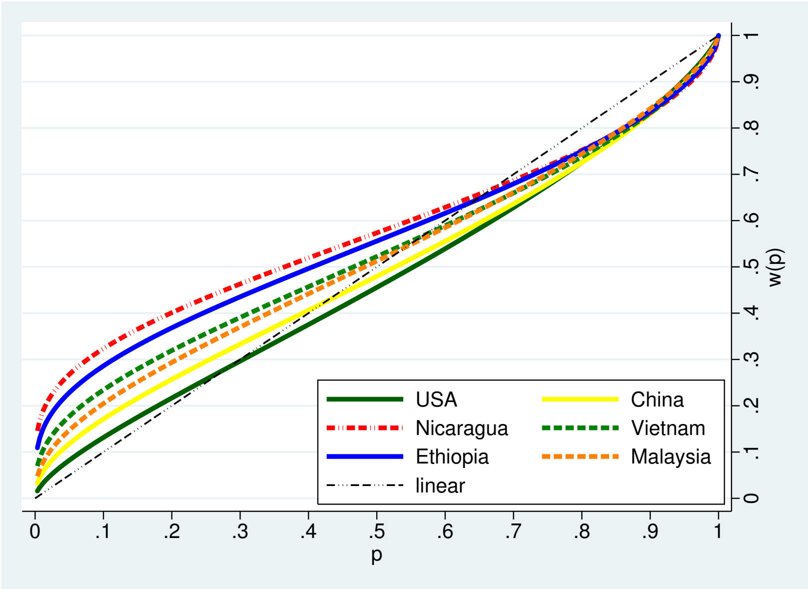
5.2 Between-country differences

We next show differences between countries. The effects shown are based on a regression with country dummies and a female dummy, added because the proportion of females differs across countries (gender effects in our data will be discussed below). Figure 3(a) shows some typical probability weighting functions for gains. The USA display the pattern hitherto thought of as typical—small probabilities are overweighed, moderate to large probabilities underweighted, and the function crosses the 45° line at around 0.3 (Wu and Gonzalez, 1996; Abdellaoui, 2000; Bleichrodt, Pinto and Wakker, 2001). While China only displays slightly less pessimism than the US (consistent with the results of Bruhin et al., 2010), other countries such as Vietnam, Ethiopia or Nicaragua have much lower degrees of pessimism.[4] The pattern here is one of increased risk tolerance, which reaches up to well beyond the midpoint of the probability scale.[5]

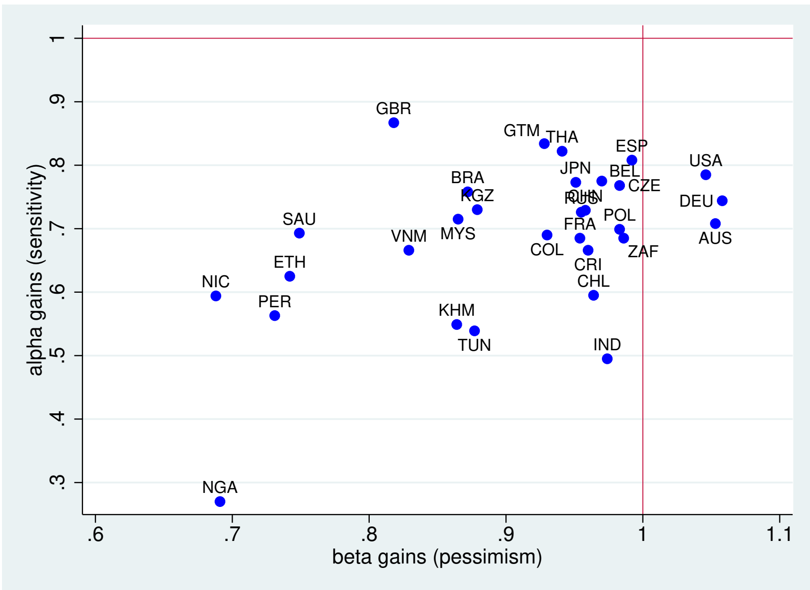
Figure 3(b) shows a scatter plot of the sensitivity and pessimism parameters. All countries show likelihood-insensitivity, with a sensitivity parameter below 0.9. Most sensitivity parameters are also at or above 0.5, with the exception of Nigeria. In terms of the pessimism parameter, Germany, Australia, and the US are the countries with the highest parameter values. They are then followed mostly by other industrialized countries such as Spain, Belgium, and Japan (although India is also far to the right). The next group to the left, roughly between a value of 0.8 and 0.9, is constituted mostly by middle income countries such as Brazil, Malaysia, Tunisia, and Vietnam (and with the UK as an exception to the middle income rule). The least pessimistic group to the far left is constituted by low-income countries such as Ethiopia, Peru, Nicaragua, and Nigeria. We find a marginally significant correlation between the sensitivity and pessimism parameters ($\rho = 0.356, p = 0.054$, Spearman rank correlation), going in the

[4] If we allow for utility curvature in addition to probability weighting, this pattern is still captured mostly in the weighting function, and not in the utility function—see Online Appendix for a detailed stability analysis.

[5] The Online Appendix provides additional analyses in this respect, including graphs showing pairwise comparison of countries with confidence bands, to show that we indeed find significant differences in terms of risk tolerance, and not only in terms of the parameters of the weighting function (which require a ceteris paribus interpretation that is not always warranted based on the empirical data).



(a) Typical weighting functions



(b) Scatter plot of parameters

Figure 3: Probability weighting functions for gains

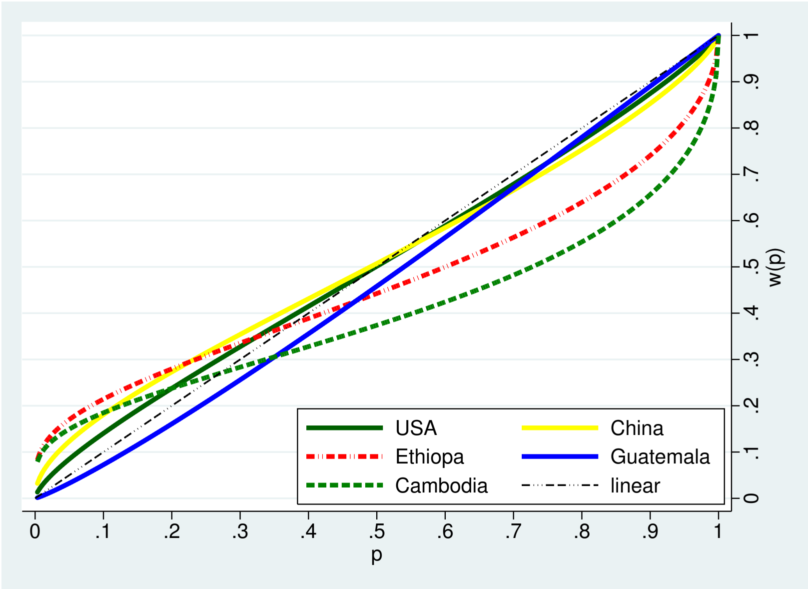
direction of more pessimistic countries exhibiting higher sensitivity.

Figure 4(a) shows typical weighting functions for losses. The patterns are less regular than for gains. In the US and China we again find a pattern of overweighting of small probabilities (now indicating risk aversion) and underweighting of large probabilities (indicating risk seeking), although the function appears to be somewhat flatter than for gains. Guatemala shows a pattern of mild risk seeking throughout. Ethiopia and Cambodia, on the other hand, have low sensitivity, which leads to substantial risk aversion for small probabilities and strong risk seeking for moderate to large probabilities. The findings are consistent with the consensus in the literature that there is less regularity for losses than for gains (Abdellaoui, 2000). Especially the data for Ethiopia and Cambodia appear to depart somewhat from previously observed functions.

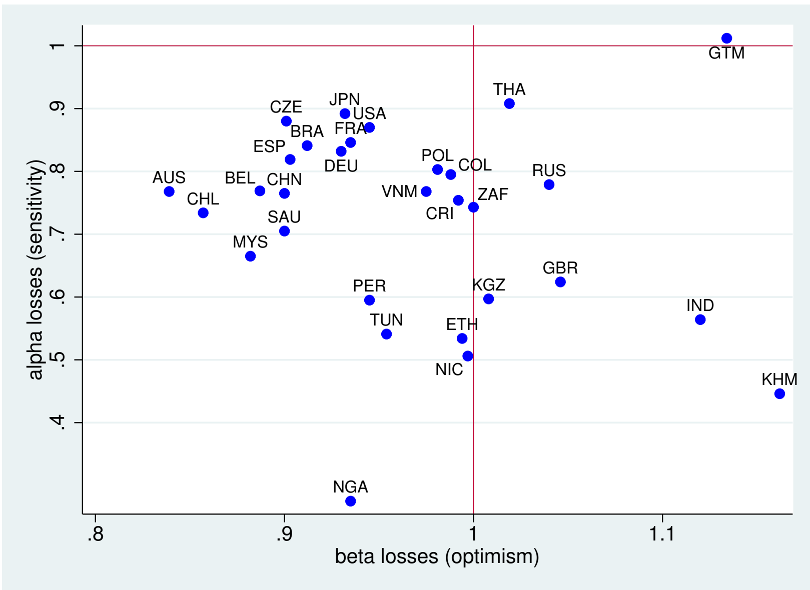
Figure 4(b) shows the parameters of the weighting function for losses in a scatter plot. Once again, most countries have sensitivity parameters between 0.9 and about 0.5. The exceptions to this rule are Guatemala, which has an almost linear function, and Cambodia and Nigeria, which exhibit extremely low sensitivity. The results for Australia show low levels of optimism, now indicated by its position to the very left in the graph. As observed for gains, there appears to be again a general tendency for poor and medium income countries to display more optimism than WEIRD countries. This tendency is, however, much less clear than for gains. We find no correlation between the optimism and sensitivity parameters ($\rho = -0.178, p = 0.347$).

5.3 Economic Indicators

Having established the main differences between countries, it is now at the time to see whether we can find some systematic relations. Prime candidates for the explanation of the differences discussed above are measures of income. Table 1 regresses the parameters of the structural model on GDP (measured as the difference of per capita GDP from the US, the richest country in our sample, in logs) and the Gini coefficient (normalized so that it is 0 for the US) as an indicator of income inequality. The regression also controls for whether a participant is a self-declared national of the country or not (foreigner). We further control for gender, which will be discussed below (the results are also stable to inserting additional demographic controls). Finally, we use a dummy to indicate whether the experiment was executed at a private university (equal to 1 for Brazil, Malaysia, Saudi Arabia, and Tunisia), and a dummy to indicate countries that are mem-



(a) Typical weighting functions



(b) Weighting parameters, scatter plot

Figure 4: Probability weighting functions for losses

bers of the petroleum-producing cartel OPEC. Private-university students may be expected to come from relatively wealthier families, so that we would expect them to be relatively more risk tolerant due to the positive correlation between income and risk tolerance generally found within countries (see Hopland, Matsen and Strøm, 2013 for a review of this correlation).[6] The OPEC dummy marks oil producing countries, in which GDP deriving from oil production does generally not accrue to the general population (this is standard in macroeconomic accounts of income levels, see e.g. Ashraf and Galor, 2011; Olsson and Hibbs, 2005).

We start by discussing the effects of GDP per capita. Sensitivity decreases with poverty for both gains and losses, whereas noise increases. Poorer countries exhibit less pessimism for gains, as well as more optimism for losses. Poor countries also tend to exhibit higher levels of loss aversion than rich countries. Being a foreigner in a country shows no effect on risk preferences. Income distribution as measured by the Gini coefficient, on the other hand, shows a strong and highly significant effect on sensitivity for losses, with more unequal countries exhibiting higher sensitivity. Subjects from private universities show lower pessimism for gains, and lower optimism for losses (marginally significant). OPEC countries have lower sensitivity for both gains and losses. They are also less pessimistic for gains, while at the same time exhibiting higher noise levels. In other words, they display the decision patterns typical of poorer countries as hypothesized, with effects aligned with those of relative poverty.

Table 1: Effects of income measures on risk preferences

N=2939, $LL = -217,069$	α^+	β^+	α^-	β^-	λ	σ
GDP difference	-0.058***	-0.063***	-0.095***	0.032***	0.194***	0.032***
	(0.007)	(0.006)	(0.008)	(0.007)	(0.024)	(0.002)
foreigner	0.026	-0.000	-0.006	0.027	-0.003	0.018**
	(0.034)	(0.031)	(0.040)	(0.029)	(0.081)	(0.007)
Gini coefficient	0.012	0.009	0.039***	0.008	-0.010	0.001
	(0.008)	(0.007)	(0.008)	(0.007)	(0.022)	(0.002)
private university	0.013	-0.064***	-0.047	-0.042*	0.091	-0.000
	(0.027)	(0.022)	(0.032)	(0.025)	(0.080)	(0.005)
OPEC	-0.264***	-0.145***	-0.270***	-0.055	0.432***	0.065***
	(0.031)	(0.025)	(0.031)	(0.034)	(0.149)	(0.006)
female dummy	✓	✓	✓	✓	✓	✓
constant	0.777***	1.010***	0.877***	0.914***	1.611***	0.157***
	(0.014)	(0.013)	(0.016)	(0.012)	(0.042)	(0.004)

* (p<0.10), ** (p<0.05), *** (p<0.01)
GDP difference indicates the difference of GDP per capita from the US in logs; i.e. relative poverty
GDP data are from the World Bank tables for 2011, measured in purchasing power parity
The Gini coefficient is the most recent before 2011 available; source: World Bank and CIA factbook

[6] This being a student subject pool, we have no measures of income at the individual level. We tried instead to obtain measures of stipends and expenses, however, the latter are extremely noisy and thus not very informative, so that we prefer not to report them here.

We may wonder whether the results presented here are stable. In particular, the correlation with GDP may be suspected of proxying for other variables. We tested this by adding a number of variables to the above regression: i) geographical variables, such as absolute latitude and whether a country is landlocked, as well as continental dummies (Gallup, Sachs and Mellinger, 1999); ii) a variety of variables indicating institutional quality (Keefer and Knack, 1997); iii) dummies indicating legal origins (Porta, Lopez-de Silanes and Shleifer, 2008); and iv) data on the genetic diversity within each country (Ashraf and Galor, 2013). GDP per capita remains highly significant in all of the regressions. The other variables at best show weak effects on risk preferences—the full regressions can be found in the Online Appendix. Analyzing the risk preference data reported in Falk et al. (2015) at the macroeconomic level, Becker, Dohmen, Enke and Falk (2015) report a strong correlation with genetic diversity (and only a much weaker correlation with GDP). This is exactly the inverse of our findings. This discrepancy may well be due to the fact that a question about one's 'willingness to take risk' captures more than just risk preferences (Vieider et al., 2015a). We do indeed find a correlation of genetic difference measures with ambiguity attitudes (L'Haridon et al., 2017), which may thus reconcile these differences in findings.

The data just presented could be driven by systematic selection effects. If students in poorer countries come systematically from relatively richer families, that may explain the strong correlation with GDP per capita. This appears not to be an issue in practice. Several papers have tested the difference between students and general population samples, generally finding no or only minor differences in aggregate risk preferences between these samples (see e.g. Andersen, Harrison, Lau and Rutström, 2010 for Denmark, and Fehr-Duda and Epper, 2012, for Switzerland). We have furthermore carried out a precise test of selection effects in our sample. Vieider, Beyene, Bluffstone, Dissanayake, Gebreegziabher, Martinsson and Mekonnen (2016) report data from an experiment conducted using the same type of tasks as employed in this paper with a representative sample of the rural population of Ethiopia—the poorest country in our sample and one of the most risk tolerant. The results clearly showed that the rural samples showed similar risk attitudes to the Ethiopian student sample. At the same time, the rural Ethiopian population sample was found to be more risk tolerant than our Western samples (see also Vieider, Truong, Martinsson and Pham Khanh, 2013 and Di Falco and Vieider, 2017, for further evidence). This clearly rejects an explanation based on systematic selection.

5.4 Individual Characteristics

Table 2 shows the effects of physical characteristics, in particular, gender, age, and height, while controlling for country effects using dummies. A large number of studies both in the economic laboratory and in the field have found gender differences in risk taking behavior (Eckel and Grossman, 2008). There remain some doubts whether gender effects are universal or whether they may vary between countries (Croson and Gneezy, 2009), and on the extent to which they may be task-specific (Filippin and Crosetto, 2015). We add to this discussion by showing evidence from a number of different countries, and by examining regularities over the probability and outcome spaces. We find women to display significantly lower sensitivity than men for both gains and losses. At the same time, women exhibit significantly higher noise levels. For gains, we also find women to be more pessimistic than men, although this effect is relatively small.

Table 2: Effects of physical characteristics on risk preferences

N=2939, $LL = -214,201$	α^+	β^+	α^-	β^-	λ	σ
female	-0.092***	0.036**	-0.072***	-0.021	-0.040	0.011***
	(0.018)	(0.016)	(0.020)	(0.016)	(0.052)	(0.004)
age	-0.008	0.002	0.009	0.016**	0.018	0.009***
	(0.009)	(0.008)	(0.009)	(0.008)	(0.022)	(0.002)
height	0.026**	-0.005	0.017	0.019**	-0.009	-0.005**
	(0.010)	(0.009)	(0.011)	(0.009)	(0.029)	(0.002)
country fixed effects	✓	✓	✓	✓	✓	✓
constant (USA)	0.767***	1.052***	0.863***	0.934***	1.616***	0.161***
	(0.032)	(0.028)	(0.038)	(0.027)	(0.088)	(0.007)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; age and height are z-scores
z-scores are used for age and height

Given the relatively narrow age range in our sample, we are reluctant to over-interpret the effect found. We replicate recent findings of physical height correlating with risk preferences (Dohmen et al., 2011). This effect goes in the direction of taller people exhibiting higher sensitivity, although this effect is significant only for gains. For losses, taller people are found to be more optimistic. Finally, taller people also have lower noise levels in their decision processes. It is not entirely clear why such effects are found for taller people. One hypothesis is that physical height, or rather its lack, may reflect diseases and socio-economic conditions in childhood (Peck and Lundberg, 1995; Maccini and Yang, 2009; Dercon and Porter, 2014).

Table 3 shows the effects of study major and grade point average (*GPA*; normalized to the same scale across countries and transformed into z-scores). GPA shows the effects we would expect to see using it as an—albeit imperfect—proxy for cognitive ability. A higher GPA is correlated with increased sensitivity for both gains and losses, as well as reduced noise levels. This is consistent with interpretations of likelihood-insensitivity as a rationality failure (Tversky and Wakker, 1995; Wakker, 2010). A higher GPA also correlates with lower levels of loss aversion. This is consistent with studies that have found that loss aversion is reduced amongst professional traders (List, 2004), and with studies that have found debiasing mechanisms such as asking subjects to give reasons for their choices to result in lower loss aversion (Pahlke, Strasser and Vieider, 2012). We also find a marginally significant positive correlation of GPA with pessimism for gains. This correlation runs counter to accounts of risk aversion resulting from low cognitive ability (Benjamin et al., 2013), but is consistent with recent criticisms of that literature (Andersson et al., 2016).

We also find significant effects of study major as measured against economics students. We find hardly any differences in risk preferences for students of mathematics and engineering, the natural sciences, or medicine. The differences obtained for students of the social sciences, the humanities, arts, and other study majors (made up mostly by law students) appear, on the other hand, to be systematic. There is a general tendency amongst these majors to display lower sensitivity. At the same time, they are more prone to errors or noise. We hypothesize that these effects are due to a lower exposure to formal mathematics, or a selection into these disciplines based on lower mathematical ability.

Table 3: Effects of study major on risk preferences

N=2939, $LL = -213,8628$	α^+	β^+	α^-	β^-	λ	σ
GPA	0.028***	0.013*	0.042***	-0.006	-0.054**	-0.007***
	(0.008)	(0.008)	(0.009)	(0.008)	(0.024)	(0.002)
math & engineering	0.005	-0.008	0.031	0.027	-0.069	-0.004
	(0.022)	(0.020)	(0.025)	(0.020)	(0.068)	(0.005)
natural sciences	-0.041	0.007	-0.070**	-0.029	-0.101	0.007
	(0.030)	(0.026)	(0.034)	(0.025)	(0.086)	(0.006)
medicine	0.026	0.000	-0.016	-0.053	-0.113	-0.001
	(0.041)	(0.037)	(0.049)	(0.037)	(0.087)	(0.008)
social sciences	-0.095***	0.026	-0.097***	-0.019	-0.027	0.018***
	(0.028)	(0.024)	(0.030)	(0.024)	(0.071)	(0.005)
humanities	-0.077**	0.001	-0.022	0.011	0.018	0.018***
	(0.031)	(0.030)	(0.037)	(0.027)	(0.091)	(0.007)
arts	-0.041	-0.052	-0.123**	0.011	0.176	0.022**
	(0.051)	(0.040)	(0.050)	(0.050)	(0.156)	(0.009)
study other	-0.068***	0.016	-0.048*	-0.016	-0.045	0.017***
	(0.024)	(0.022)	(0.027)	(0.022)	(0.065)	(0.005)
physical characteristics	✓	✓	✓	✓	✓	✓
country dummies	✓	✓	✓	✓	✓	✓
constant	0.777***	1.038***	0.858***	0.947***	1.705***	0.159***
	(0.035)	(0.032)	(0.041)	(0.031)	(0.101)	(0.008)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

social sciences exclude economics students, who serve as reference

Finally, we can address the effect of cultural variables on risk preferences. Some of the previous literature has emphasized accounts based on survey measures of cultural attitudes (Hofstede, 1980). For instance, Weber and Hsee (1998) compared four countries using hypothetical certainty equivalents for 50-50 prospects. They organized the results using the individualism-collectivism dimension, and concluding that relatively collectivistic societies such as China or Poland exhibit lower risk aversion compared to Germany and the US because of the implicit insurance provided by the closer social fabric. Notice, however, how their findings are also consistent with GDP differences. Rieger et al. (2015) explained risk preferences obtained in a survey with economics students in a large number of countries mostly based on uncertainty avoidance, another of the Hofstede cultural scales. In a companion paper, Wang, Rieger and Hens (2016) explain cross country differences in loss aversion again through the Hofstede scales, although in this case it is mostly through masculinity and individualism. Somewhat surprisingly, we find virtually no explicative power of Hofstede's cultural scales—details are provided in the Online Appendix.

Another cultural dimension that has received some attention in the literature on risk preferences is religious affiliation. Results obtained so far are not consistent. Some researchers have concluded that Protestants are less risk averse than Catholics (Dohmen et al., 2011), while others have reached the opposite conclusion (Noussair, Trautmann, van de Kuilen and Vellekoop, 2013). There is little evidence on religions other than the Judeo-Christian ones prevalent in the West. We find no difference between Catholics and Protestants in our data. While we find some differences for other religious affiliations, such as e.g. Jews being less risk averse than Protestants for gains (see also Barsky, Kimball, Juster and Shapiro, 1997), these correlations are not systematic and likely spurious. The regressions and a discussion of the results are presented in the Online Appendix.

6 Explained and unexplained heterogeneity

In this last section of the results, we take a closer look at overall preference heterogeneity based on our random parameter estimates described in equation 12. We thereby focus on developing intuition based on graphs of parameter distributions, and on discussing the most important insights deriving from this analysis. More detailed statistical results can be found in the Online Appendix.

We start by discussing overall heterogeneity in risk preferences, and in particular likelihood-dependence and reference-dependence. We find considerable heterogeneity for all preference parameters. Likelihood-insensitivity appears to be the norm. For gains, the distribution implies that 82% of our subjects have a sensitivity parameter below 1, with only 12% of subjects characterized by a sensitivity value close to 1 (i.e with α^+ lying in the range $[0.9; 1.1]$). For losses, 76% of the population have a sensitivity parameter below 1 and 14% of subjects have a sensitivity value close to 1. We also find considerable heterogeneity in loss aversion. The parameter estimates correspond to a distribution with a median value of 2, very close the value estimated above.[7] This distribution implies that

[7]The Online Appendix reports correlations between the point estimates at the country level using the approach from the first part of the median values obtained from the random parameter estimates at the same level, and shows that they are highly correlated. This proves the consistency of the two approaches.

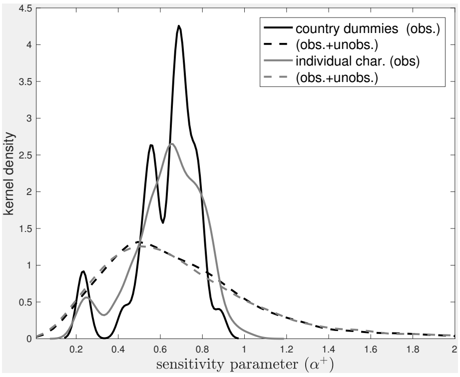
94% of the loss aversion parameters fall in the range $[1; 5]$, and corresponds to the usual benchmarks used in the literature (Barberis, 2013).

We now proceed to comparing the overall heterogeneity in preference parameters estimated across all individuals to formulations of our random parameter model that allow us to visualize heterogeneity across observable characteristics. We proceed as follows. We start by estimating a model with only country dummies to capture differences between countries. By definition, such a model captures all of the between-country variance. We then use this model as a benchmark case to discuss individual and macro-economic characteristics. In particular, we are interested in how much more of the overall heterogeneity in preference parameters we can explain by adding a large set of observable individual characteristics. When it comes to the macro-economic characteristics, our interest lies in how much of the heterogeneity captured by country dummies can be explained when using a smaller number of country characteristics such as GDP instead.

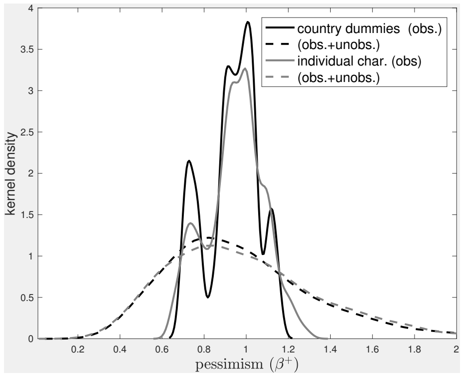
Figure 5 compares the heterogeneity captured by the country dummies to the heterogeneity captured by country dummies plus individual characteristics. The outermost curves represent the overall heterogeneity in the two estimations.[8] Adding country dummies by definition explains all of the heterogeneity across countries. The proportion of overall heterogeneity explained by the country dummies remains, however, quite modest. This shows that there is more heterogeneity across individuals than across countries, albeit with quantitative differences across parameters. The country dummies capture relatively little of the overall heterogeneity for the pessimism/optimism parameters, with 13.3% of the variance in pessimism for gains explained by the country dummies, and only 6.4% of the variance in optimism for losses. This increases to over 30% for the sensitivity parameters, with similar figures obtaining for loss aversion and noise.

Further adding individual characteristics to the regression does not increase the explained variance by much, as is apparent from figure 5. Notwithstanding

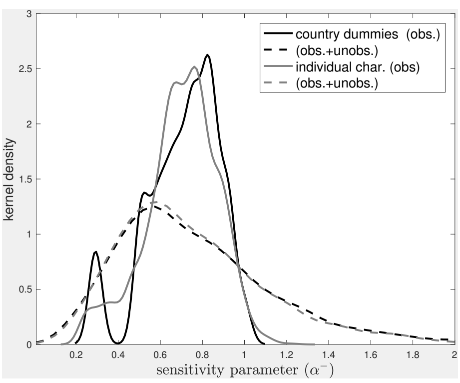
[8]There are two such curves, corrsponding to the estimations with and without individual characteristics added. The two differ slightly, and we show them both for reasons of precision. The two curves, however, can be seen to largely coincide, and indeed there are no significant differences between them.



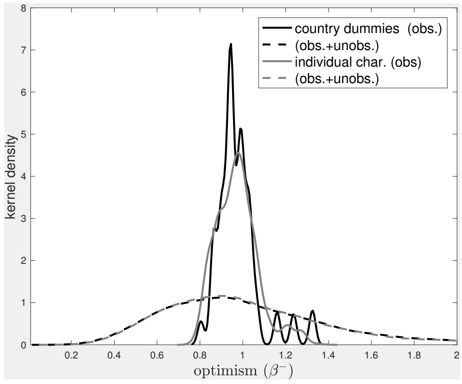
(a) Sensitivity gains



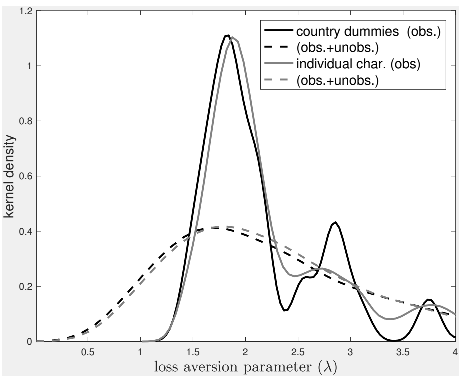
(b) Pessimism gains



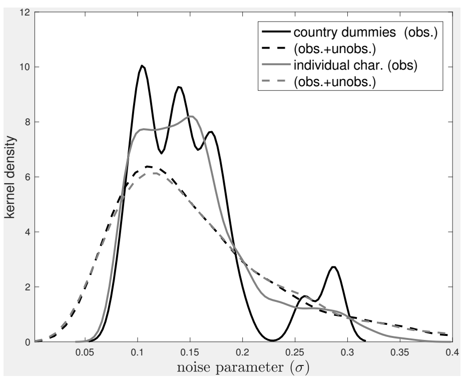
(c) Sensitivity losses



(d) Optimism losses



(e) Loss aversion



(f) Noise

Figure 5: Observable versus unobservable heterogeneity, individual characteristics
Dashed lines are estimated parameter distributions taking observed and unobserved heterogeneity into account. Solid grey lines represent the observed heterogeneity only and neglect the unobserved part. Densities are kernel density estimates over individuals.

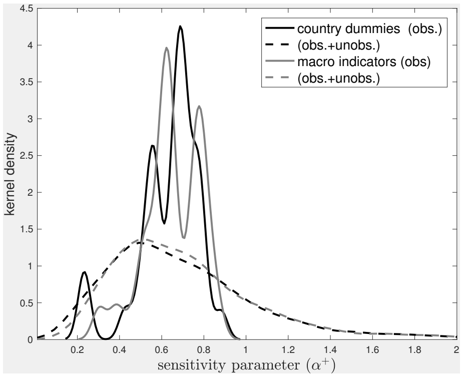
our more flexible model, which can account for a richer array of within-subject heterogeneity through reference-dependence and likelihood-dependence, our conclusions thus remain remarkably similar to those reached by von Gaudecker et al. (2011). Observable characteristics at the individual level contribute little to explaining overall heterogeneity in risk preferences.

This narrative changes once we start examining to what extent we can explain between-country heterogeneity recurring to a few macroeconomic indicators rather than to country-specific dummies. Specifically, we will use the macroeconomic indicators used above, that is, GDP per capita, the Gini coefficient, and the private university and OPEC dummies. We also control for female since the proportion of females in the experiment differs between countries. Figure 6 shows the distribution of parameters estimated based on macroeconomic indicators, and again compares this to the benchmark of heterogeneity captured by country dummies. Just like above, the outermost curves represent the overall heterogeneity in the two estimations, while the peaked curves correspond to distributions of preference parameters implied by the observed covariates only. Comparison between the two peaked curves shows what is lost in terms of explained heterogeneity when moving from country dummies to macroeconomics indicators.

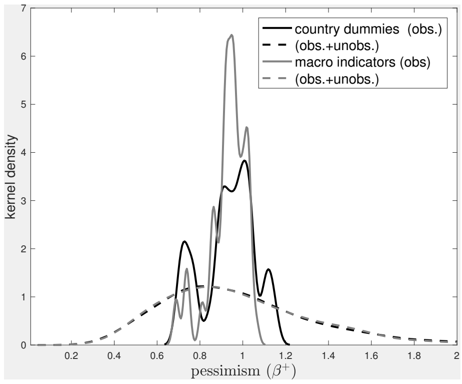
While obviouslly capturing less heterogeneity than the country dummies, the macroeconomic variables capture a substantial part of that heterogenity, ranging from 43% to 70% of the heterogeneity captured by country dummies. Once again, this exercise is least successful for pessimism and optimism, although still capturing more than half of the variance captured by country dummies for pessimism and close to 40% for optimism (see Online Appendix for the exact figures). This stands in contrast to the effect found for the individual characteristics. We thus conclude that while the characteristics we observe at the individual level explain only a very small part of the overall heterogeneity between individuals, macroeconomic characteristics pick up on most of the between country differences.

7 Conclusion

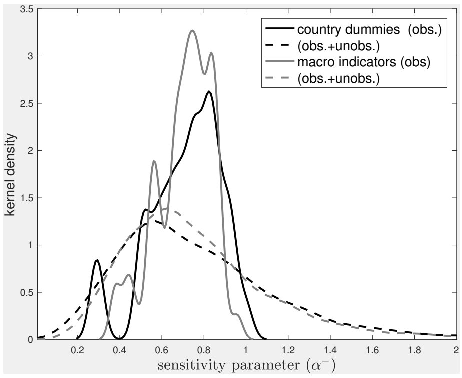
We used data from 30 countries and 2939 subjects to systematically examine differences in risk preferences across individuals and countries. Notwithstanding the flexible descriptive model of choice under risk, observable characteristics



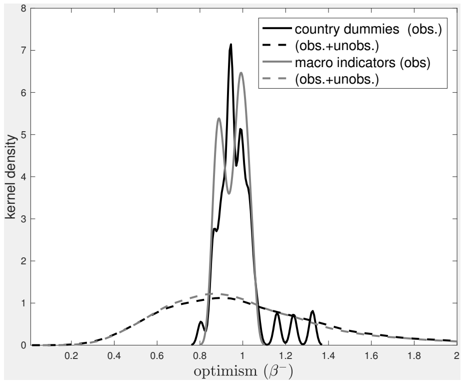
(a) Sensitivity gains



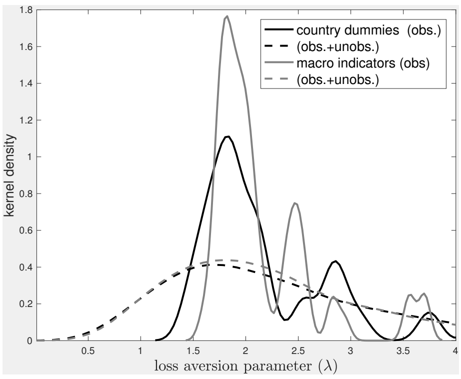
(b) Pessimism gains



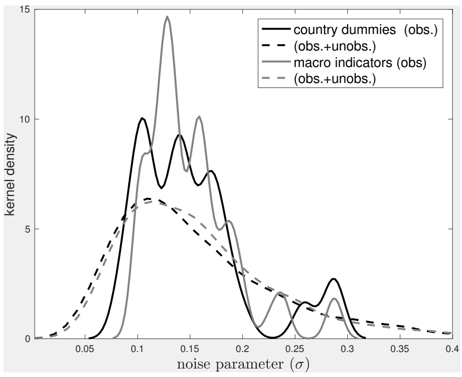
(c) Sensitivity losses



(d) Optimism losses



(e) Loss aversion



(f) Noise

Figure 6: Observable versus unobservable heterogeneity, country-specific dummies and macroeconomic indicators

Light grey lines are estimated parameter distributions taking observed and unobserved heterogeneity into account. Dark grey lines represent the observed heterogeneity only and neglect the unobserved part. Densities are kernel density estimates over individuals.

were found to explain little of the total heterogeneity in preference parameters. This may be an indication that risk preferences constitute an individual trait that is largely independent of observable characteristics of the decision maker.

Macroeconomic characteristics of countries, on the other hand, could capture a large proportion of the overall between-country heterogeneity. We further excluded systematic selection effects by showing that the effects found in the poorest country in our sample, Ethiopia, carries over to a representative sample of the rural population of that country (Vieider et al., 2016).

In terms of country-level data, we observed both universal patterns and systematic differences. In particular, we found the qualitative patterns of likelihood-insensitivity and reference-dependence to be universal, albeit with some quantitative differences between countries. Therefore, we would expect the economic phenomena related to probability weighting and sign-dependence, such as for example the disposition effect, overweighting of small-probability losses in insurance choices, and many of the anomalies observed in behavioral finance, to be universal. The most important difference between countries consisted in poorer countries showing systematically higher levels of risk tolerance than richer countries. This finding is indeed surprising, since scholars have to date generally assumed poor countries to be *less* risk tolerant based on within-country results showing risk aversion to decrease in income or wealth (see e.g. Haushofer and Fehr, 2014, for a recent literature review reaching that conclusion).

In terms of observable characteristics, we could replicate and further qualify typical findings in the literature, such as gender effects and effects of physical height. Indeed, while there is a considerable literature discussing the effect of such characteristics on overall risk aversion (Croson and Gneezy, 2009; Dohmen et al., 2011; Filippin and Crosetto, 2015), we have shown that the strongest effects register in terms of reduced sensitivity for women. We drew similar conclusions for GPA, which again was found to correlate most strongly with sensitivity. The latter results seem in agreement with conclusions presented by Andersson et al. (2016), according to which cognitive ability influences mostly error terms, but shows no correlation with overall preferences if choice lists are balanced.

This leaves the question of what may be ultimately driving the negative between-country correlation of aggregate risk tolerance with GDP per capita. The latter may appear puzzling in light of the prevalent finding of a positive correlation between risk tolerance and income at the individual level (Donkers, Melenberg and Van Soest, 2001; Dohmen et al., 2011; Gloede, Menkhoff and Waibel, 2015; Hopland et al., 2013; Vieider et al., 2013; 2016). Several recent papers have modeled economic growth as a function of risk tolerance (Galor and Michalopoulos, 2012; Doepke and Zilibotti, 2014; Klasing, 2014). In these models, risk preferences are endogenously shaped by market forces, and the models of Galor and Michalopoulos (2012) and Doepke and Zilibotti (2014) in particular predict the type of relationship between risk tolerance and GDP per capita found in this paper (see Bouchouicha and Vieider, 2017b, for a detailed discussion). More research is needed in order to determine which mechanism in particular may be driving these effects.

A Characteristics country by country

Table A.1: Number of subjects per country and principal characteristics

country	Sub.s	For.s	age	male	econ	math	natural	hum	arts	social	PPP/€	language	University	GDP	Gini
Australia	61	6	25.41	0.656	0.262	0.180	0.131	0.098	0.049	0.033	2 AUD	English	University of Adelaide	39,466	.305
Belgium	91	13	20.64	0.451	0.418	0.055	0.088	0.066	0.022	0.132	€1	French	University of Liege	38,633	.280
Brazil	84	1	20.86	0.683	0.964	0.000	0.000	0.012	0.000	0.000	2 Real	Portuguese	Escola de Administraão, São Paolo	11,719	.547
Cambodia	80	0	20.74	0.375	0.000	0.212	0.237	0.125	0.175	0.175	1500 Riel	Khmer	University of Phnom Penh	2,373	.444
Chile	96	0	21.46	0.479	0.000	0.000	0.229	0.000	0.000	0.260	500 Pesos	Spanish	Universidad de Conception	17,125	.521
China	204	0	21.55	0.608	0.127	0.451	0.181	0.083	0.005	0.064	4 RMB	Chinese	Jiao Tong, Shanghai	8,442	.480
Colombia	128	0	21.21	0.500	0.062	0.797	0.047	0.031	0.023	0.008	1500 Pesos	Spanish	Universidad de Medellin	10,103	.560
Costa Rica	106	5	22.71	0.666	0.292	0.179	0.113	0.009	0.019	0.132	500 Colones	Spanish	Universidad de Costa Rica, San Jose	12,236	.503
Czech Rep.	99	2	22.38	0.606	0.485	0.111	0.051	0.121	0.030	0.091	20 Kronas	Czech	Charles University, Prague	25,949	.310
Ethiopia	140	1	21.14	0.657	0.593	0.107	0.079	0.021	0.000	0.093	6 Birr	English	Addis Ababa University	1,116	.300
France	93	8	21.30	0.527	0.430	0.054	0.022	0.043	0.032	0.032	€1	French	University of Rennes 1	35,194	.327
Germany	130	32	26.52	0.515	0.115	0.400	0.108	0.115	0.008	0.023	€1	German	Technical University, Berlin	39,414	.270
Guatemala	84	1	22.20	0.464	0.345	0.179	0.000	0.119	0.036	0.131	6 Quetzales	Spanish	Universidad Francisco Marroquín	4,961	.559
India	89	0	21.01	0.303	0.697	0.000	0.022	0.112	0.090	0.034	22 Rupees	English	University of Kolkata	3,650	.368
Japan	84	0	21.74	0.512	0.095	0.417	0.107	0.107	0.000	0.048	120 Yen	Japanese	Hiroshima Shudo University	34,278	.376
Kyrgyzstan	97	2	20.02	0.485	0.639	0.000	0.000	0.072	0.000	0.289	25 KGS	Russian	University of Bishkek	2,424	.362
Malaysia	64	0	20.09	0.578	0.578	0.188	0.062	0.000	0.016	0.047	2 Ringgit	English	University of Nottingham Malaysia	15,589	.462
Nicaragua	120	1	20.94	0.550	0.917	0.025	0.000	0.000	0.000	0.000	10 Córdobas	Spanish	Universidad National Autonoma	2,940	.405
Nigeria	202	2	22.65	0.495	0.406	0.000	0.005	0.054	0.312	0.119	110 Naira	English	University of Lagos	2,532	.437
Peru	95	1	23.66	0.463	0.579	0.368	0.000	0.011	0.000	0.042	2 N. Soles	Spanish	Instituto del Peru	10,318	.460
Poland	89	1	24.00	0.517	0.427	0.079	0.067	0.169	0.000	0.124	2.4 Zloty	Polish	University of Warsaw	21,281	.341
Russia	70	8	20.56	0.500	0.729	0.129	0.000	0.086	0.000	0.014	22 Rubles	Russian	Higher School of Economics	21,358	.420
Saudi Arabia	65	12	21.74	1.000	0.585	0.308	0.000	0.000	0.000	0.000	4 Riyal	English	King Fahd University	24,434	.570
South Africa	71	18	22.44	0.606	0.451	0.254	0.056	0.056	0.014	0.042	8 Rand	English	University of Cape Town	11,035	.650
Spain	80	3	20.94	0.513	0.450	0.037	0.000	0.100	0.037	0.225	€1	Spanish	Universidad Pompeu Fabra	32,701	.320
Thailand	79	0	20.59	0.354	0.329	0.101	0.139	0.000	0.013	0.215	20 Baht	Thai	University of Khon Kaen	8,703	.536
Tunisia	74	0	22.26	0.527	0.230	0.473	0.081	0.000	0.000	0.000	2 Dinar	French	Universite Libre de Tunis	9,415	.400
UK	80	0	20.77	0.450	0.700	0.000	0.025	0.013	0.025	0.075	1 Pound	English	King's College London	36,511	.350
USA	97	22	21.32	0.495	0.144	0.206	0.113	0.041	0.031	0.186	$ 1	English	University of Michigan Ann Arbor	48,442	.450
Vietnam	87	0	20.20	0.575	0.667	0.057	0.034	0.000	0.011	0.023	8000 Dong	Vietnamese	Ho-Chi-Minh-City University	3,435	.357
Total	2939	139	21.83	0.530	0.402	0.189	0.069	0.056	0.040	0.089					

Sub.s stands for number of subjects, For.s for number of foreigners; econ etc. indicate study majors; PPP/€indicates exchange rates in purchasing power parity used for conversion
Gini coefficients are taken from the World Bank where available, else from the CIA World Factbook; 2011 or closest available
GDP refers to 2011 values in PPP, current US Dollars; source: World Bank

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