What loss aversion?
The implications of modelling choice in estimations under risk*

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Abstract

Estimating loss aversion involves a two-step procedure: estimating utility for gains and losses; then identifying loss aversion using these estimates. The existing literature employs many different theoretical definitions that differ widely in their assumptions and there is little agreement on the empirical strength and correlates of loss aversion. We use a unique cross country data set to study the effects of adopting six common theoretical definitions and a behavioural definition on the resulting estimate of loss aversion. Our findings suggest that empirical estimates of loss aversion differ widely depending on the definition adopted. These differences are driven by how behaviour observed in prospects featuring pure gains and losses translate into estimated parameters that feed into the definition of loss aversion, as opposed to behaviour in mixed prospects. We also demonstrate that correlation patterns between observable characteristics, such as gender, and loss aversion are highly sensitive to the adopted definition.

Keywords: loss aversion; risk preferences; prospect theory; gain-loss separability

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1 Motivation

People tend to dislike symmetric bets over gains and losses. Recognising this fundamental aspect of human decision making, Markowitz (1952) proposed to measure utility relative to the current asset position, and suggested that "the curve falls faster to the left of the origin than it rises to the right of the origin" (p. 154). Kahneman and Tversky (1979) incorporated this concept known as *loss aversion* into prospect theory, the main descriptive theory of decision making today (Barberis, 2013; Starmer, 2000). The concept of loss aversion has been invoked to explain a staggering variety of behaviour observed in the real world, from short-sighted investment patterns (Gneezy and Potters, 1997) to labour supply decisions (Camerer, 2000; Goette, Huffman and Fehr, 2004), and the disparity between willingness-to-pay and willingness-to-accept (Bateman, Kahneman, Munro, Starmer and Sugden, 2005). It is also of prime importance in understanding decision making processes for entrepreneurs and investors, and has been shown to affect professional traders (Haigh and List, 2005).

Despite the frequency in which loss aversion is used to qualitatively account for behaviour, there is little agreement on the strength of loss aversion. While the value of 2.25 estimated by Tversky and Kahneman (1992) is often taken as a canonical reference, in practice estimated parameters differ widely. Estimates range from no or very weak evidence for loss aversion (Brooks, Peters and Zank, 2014; Harrison and Rutström, 2009; Schmidt and Traub, 2002) to findings indicating that losses loom about three and a half times as large as gains (Liu, 2012; Nguyen, 2011). It is difficult to determine the cause of these differences in estimates because each paper adopts an alternative definition of loss aversion and uses data gathered from different countries. Gaining a better understanding of the determinants of these differences is an step in progressing towards an agreed upon value of loss aversion, and can impact prescriptive work, as well as empirical work adopting typical parameter estimates from the experimental literature as a 'standard value' (e.g., Benartzi and Thaler, 1995).

We systematically compare loss aversion coefficients estimated according to six common definitions, that emerge naturally from structural estimation of reference dependent preferences. These estimates are compared to a nonparametric, behavioural definition that captures general risk preferences over mixed gain loss prospects. The main models used are original prospect theory (Kahneman and Tversky, 1979), cumulative prospect theory (Tversky and Kahneman, 1992), and reference-dependent expected utility theory (Markowitz, 1952). For each model we estimate an additional variation that results from common assumptions or parameter restrictions. Our approach is complementary in nature to Abdellaoui, Bleichrodt and Paraschiv (2007) who estimated loss aversion non-parametrically, thus avoiding issues deriving from functional form choice. They compared different local approximations of loss aversion using curvature of utility around the reference point under one model (what we refer to as original prospect theory), uncovering considerable differences in parameter values across approximations. Our focus is different and complements the findings of Abdellaoui et al. (2007). Rather than comparing theoretical definitions within one model, we compare estimates under a common estimation procedure but across different models of choice under risk. We then trace the differences in our estimates back to the fundamental parameters of the encapsulated choice models and their values under the different modelling assumptions.

Loss aversion is usually empirically identified by the combination of several choice lists in the pure gain and loss domains with at least one mixed gain-loss prospect (Abdellaoui, Bleichrodt and L'Haridon, 2008). This procedure is justified by gain-loss separability, an axiom in prospect theory requiring that the valuation of a given mixed prospect be composed of the separate valuations for its gain and loss components. Wu and Markle (2008) showed that gain-loss separability is violated empirically under some circumstances. They concluded that probabilities may be largely ignored in mixed prospects, leading to flatter probability weighting functions in the mixed gain-loss outcome domain than for gains and losses separately. Baltussen, Post and Vliet (2006) found violations of cumulative prospect theory in mixed prospects that could also be driven by failures of gain-loss separability—although probabilities would need to be treated more linearly in the mixed domain to account for their findings. This evidence casts doubt on the accuracy of estimates of loss aversion coefficients that are identified in large parts by behaviour in pure gain and pure loss prospects.

Independent of potential concerns regarding the validity of gain-loss separability, the estimated loss aversion parameter may depend subtly on the general modelling assumptions adopted under different choice theoretic frameworks. For instance, loss aversion is increasingly incorporated into reference-dependent formulations of expected utility theory in both theoretical and empirical work (Diecidue and van de Ven, 2008; Kőszegi and Rabin, 2007; Sugden, 2003; von Gaudecker, van Soest and Wengström, 2011).

Since utility curvature estimated assuming expected utility theory is generally different from utility curvature under prospect theory (Bleichrodt, Abellan-Perpiñan, Pinto-Prades and Mendez-Mart 2007; Schmidt and Zank, 2008), this will in turn have an impact on loss aversion coefficients estimated under different models. Even under prospect theory, several models of loss aversion coexist in the literature (Schmidt and Zank, 2005), which could impact the estimated parameter values.

We use data obtained in identical experiments with 2939 subjects in 30 countries to explore the impact of adopting different definitions of loss aversion on the resulting estimate. The advantage of our multi-country data set is two fold:. First, the data show considerable variability in risk preferences across countries for both gains and losses (Vieider, Chmura and Martinsson, 2012; Vieider, Lefebvre, Bouchouicha, Chmura, Hakimov, Krawczyk and 2015a).[1] This variability provides a unique testbed for how differences in utility curvature for gains and losses feed back into the estimates of loss aversion assuming gain-loss separability holds. We can then investigate how much behaviour from pure gain/loss prospects influences the estimate of loss aversion compared to actual decisions in mixed prospects. Second, the cross country nature of our data set allows investigation into how loss aversion differs across countries, and how sensitive this findings are as we move across definitions. In addition, the large sample size allows allow us to examine whether different definitions impact the correlates of loss aversion, using a variety of individual and country-level variables.[2]

We find that different modelling assumptions result in estimates of loss aversion that differ in magnitude in both a statistical and economics sense. We trace these differences back to differences in the fundamental parts of the loss aversion definitions, in particular the ratio of utility curvature for gains and losses (as well as the ratio of decision weights in some models). Parameters estimated over gains and losses are found to drive most of the between-country differences in loss aversion under all six definitions, while behavioural loss aversion is found to be relatively similar across countries. Our results demonstrate that loss aversion estimated assuming gain-loss separability may

[1] See also Rieger, Wang and Hens, 2014 for a related finding with hypothetical willingness to pay for gain and loss lotteries across a large number of countries.

[2] These data are used in several papers, but the contributions of the different papers are clearly distinct. Vieider et al. (2012) and Vieider et al. (2015a) only report measures for gains and losses, and do not discuss the mixed prospect at all. L'Haridon and Vieider (2015) use the same data set for the estimation of prospect theory parameters including loss aversion. However, they only use one specific definition of loss aversion that naturally emerges from their structual model. We will further put the different findings in context in the discussion.

overestimate the actual impact of preferences over gains and losses on behaviour in the mixed prospects, shedding further doubt on the assumption. We also document the important role played by the definition of loss aversion we adopt and correlation with observable characteristics. For instance, women are found to have higher loss aversion than men according to the behavioural definition. This changes radically under the other definitions. We find no evidence of a gender effect for four other definitions; whilst for two other definitions, we even find *significant effects in the opposite direction*, with women estimated to be *less* loss averse than men. This effect can be traced to gender effects for gains and losses impacting loss aversion under gain-loss separability. In sum, our findings show the benefit of our model-free behavioural measure as a benchmark.

This paper proceeds as follows. Section 2 presents the general theoretical setup and discusses the different modelling assumptions underlying the six-plus-one definitions of loss aversion used. Section 3 describes the experiment and data, and section 4 details our econometric approach and stochastic assumptions. Section 5 shows the results, starting from aggregate estimates, and then moving on to between-country heterogeneity, and finally individual characteristics. Section 6 discusses the implications of our findings and in conclusion proposes pragmatic solutions to some of the issues encountered.

2 Definitions of loss aversion in structural models

We implement definitions of loss aversion that arise from three popular models of decision under risk that incorporate loss aversion—original prospect theory (OPT), cumulative prospect theory (CPT), and reference-dependent expected utility theory (EUT). For each of these models we estimate a flexible specification and a restricted specification. The restrictions take the form of imposing constraints on parameters or behavioural restrictions on an individual's decision process for mixed prospects. Each of the restrictions leads to a different measure of loss aversion found in the existing literature. In addition to these theory-based measures, we use a 'behavioural' measure of loss aversion as a benchmark. The latter captures behaviour in the mixed prospect in a straightforward manner without relying on any modelling assumptions, but it comes at the cost of theoretical accuracy. Before explaining each definition of loss aversion in detail, we provide the underlying primitives common to all the definitions.

Modelling preliminaries

We focus our analysis on individual decisions over binary prospects $\xi = (x, p; y)$, where the outcome x obtains with a probability p, and the outcome y obtains with a complementary probability $1 - p$. Outcomes are modelled as changes in asset positions relative to a status quo of zero throughout. Individual decision makers face three kinds of prospects: pure gain prospects ($x > y \geq 0$), pure loss prospects ($0 \geq y > x$) and mixed prospects ($x > 0 > \ell$). Following the experimental set-up described in further detail below we assume the objective probabilities attributed to gains, losses, and mixed prospects to be constant at $p \equiv 0.5$. Outcomes are subjectively transformed into utilities via a utility function $v(\cdot)$, which satisfies $v(0) = 0$ and which is assumed to be monotonically increasing in outcomes. Probabilities are subjectively transformed into decisions weights $\pi^j \equiv w^j(0.5)$, where $w(\cdot)$ indicates an increasing probability weighting function satisfying $w^j(0) = 0$ and $w^j(1) = 1$, and $j = \{+, -\}$ indicates that decision weights are allowed to differ between gains and losses. Estimating a single decision weight instead of a full probability weighting function has the advantage that we do not need to make any assumptions about the functional form of the probability weighting function (Abdellaoui et al., 2008). The decision weight is then just one additional parameter to be estimated. For pure gains or losses, the utility of a prospect can be represented as follows:

$$U(\xi) = \pi^j v(x) + (1 - \pi^j) v(y). \tag{1}$$

For mixed prospects, the utility of a prospect takes the following form:

$$U(\xi) = \pi^+ v(x) - \lambda \pi^- v(\ell) \tag{2}$$

where ℓ represents the loss amount, and λ is the parameter capturing loss aversion. We write this parameter into the general equality instead of the utility function as is customary because of its central position in this analysis.

We use an exponential utility function throughout. The choice of exponential utility results from two important shortcomings of the alternative power utility formulation. First, joint estimation of decision weights and utility curvature under power utility suffers from high degrees of collinearity, making it hard to separately identify them. In addition, the use of a normalised exponential function solves common issues encountered when using domain-specific power utility in the estimation of loss aversion parameters. In particular, the estimated loss aversion parameter may depend on the scaling of outcomes—see Wakker (2010), section 9.6, for a detailed discussion. Utility takes the following form:

$$v(x) = \begin{cases} \frac{1-\mathrm{e}^{-\mu x}}{\mu} & \text{if } x > 0 \\ \frac{1-\mathrm{e}^{-\nu(-x)}}{\nu} & \text{if } x \leq 0 \end{cases} \tag{3}$$

where μ determines utility curvature for gains, with $\mu \geq 0$ indicating concavity and $\mu \leq 0$ convexity of the utility function; and ν determines curvature for losses, with $\nu \geq 0$ indicating convexity and $\nu \leq 0$ concavity.

Empirically, the utility function and decision weights are identified from equation 1 using pure gain and pure loss prospects. Once these quantities are identified, equation 2 allows for the identification of loss aversion, since λ remains the only parameter to be assessed. Wu and Markle (2008) called into question the empirical validity of gain-loss separability, the principle underlying this kind of two-step procedure. In particular, they found probabilities in mixed prospects to be largely ignored, resulting in a flatter probability weighting function for mixed prospects than for prospects in the pure gain and pure loss domains. Our focus will rather be on utility, and on the extent to which various modelling assumptions underlying the structural model itself impact the estimated loss aversion coefficients once gain-loss separability is imposed. In doing so, we provide a systematic appraisal of how alternative modelling assumptions feed through the structural estimation and (potentially) drive differences in empirical results.

Definitions of loss aversion: Cumulative prospect theory

All definitions of loss aversion in the present paper descend from the general theoretical setup above, generally by restricting some of the parameters in either the complete model constituted of equations 1 and 2, or for equation 2 only. The definition of loss aversion directly resulting from the flexible modelling set-up described above is the CPT definition (Tversky and Kahneman, 1992). Under CPT individual decisions over risky prospects are influenced by utility over outcomes and decision weights assigned to probabilities. Since decision weights are allowed to differ for gains and losses in the model, i.e. in principle $\pi^+ \neq \pi^-$, they form integral part of the definition of the loss aversion parameter (Schmidt and Zank, 2005; Zank, 2010). Since in our setup ℓ is elicited in such a way as to make a decision maker indifferent between the mixed prospect and the status quo, the CPT definition emerges simply by rearranging equation 2:

$$\lambda_{\text{CPT}} = \frac{\pi^+}{\pi^-} \frac{v(x)}{v(\ell)} \tag{4}$$

It is evident that loss aversion under the general CPT model is determined jointly by the relative slope of the utility function for gains and losses, and by the ratio of the decision weights. Notice that even if loss aversion is the predominant pattern based on the utility ratio, $v(x)/v(\ell) > 1$, a small enough ratio of decision weights may result in 'loss neutrality' with $\lambda_{CPT} \approx 1$ or even 'gain seeking', i.e. a loss aversion coefficient smaller than 1. Because this definition naturally arises out of the CPT model, this type of definition is amongst the most commonly implemented in structural estimations of prospect theory (Beauchamp, Benjamin, Chabris and Laibson, 2012; Booij, Praag and Kuilen, 2010; Harrison and Rutström, 2009).

A special case of the CPT definition (4) involves a linear utility specification (LU) in combination with subjectively distorted probability weights. Taking the loss aversion definition under CPT in equation (4), and setting $v(x) \equiv x$ so that utility becomes piecewise linear, we get a new definition of loss aversion:

$$\lambda_{\text{LU}} = \frac{\hat{\pi}^+}{\hat{\pi}^-} \frac{x}{\ell} \tag{5}$$

where the 'hat' over the decision weights serves to remind us that the weights will be generally different from those in equation (4). This formulation is much rarer in the existing literature. It is the result of adapting the dual theory of decision making under risk (Yaari, 1987) to reference-dependent formulations such as prospect theory (Schmidt and Zank, 2007). An advantage of this formulation consists in avoiding issues of collinearity between utility curvature and decision weights (Zeisberger, Vrecko and Langer, 2012), which can make results cumbersome to interpret in terms of risk preferences, especially when regressing the model parameters on observable characteristics of decision makers. This formulation can be useful in analysis conducted with relatively small monetary values as typically used in experiments, since utility for such amounts should be approximately linear (Wakker, 2010). L'Haridon and Vieider (2015) use this definition of loss aversion in their structural estimations using the same data, and we report it to facilitate comparability between our results.

Definitions of loss aversion: Original prospect theory

Definitions of loss aversion under CPT described above have the feature that risk preferences as captured in decision weights form an integral part of the definition. A potential drawback of these definitions is that the inclusion of decision weights makes loss aversion under risk a different concept from loss aversion under certainty (Gächter, Johnson and Herrmann, 2010; Kahneman, Knetsch and Thaler, 1991). The definition also seems at odds with empirical investigations finding reduced sensitivity to probabilities in the mixed domain (Wu and Markle, 2008), since it imposes probability weighting estimated for pure gains and losses on mixed-domain choices. Under OPT (Kahneman and Tversky, 1979), decision weights play no role in the definition of the loss aversion parameter (Schmidt and Zank, 2005). The definition in (4) thus simplifies to:

$$\lambda_{\mathrm{OPT}} = \frac{\hat{v}(x)}{\hat{v}(\ell)} \tag{6}$$

This 'utility ratio' definition can arise from OPT due to two different principles encapsulated in that theory. The first principle is the equality of decision weights for gains and losses, $\pi^{+} \equiv \pi^{-}$. Under this assumption, solving equation (2) for λ the two probability weights simply cancel out of the equation.[3] We refer to this case as *OPT equal weights*. The 'hat' over the utility symbol again serves to remind us that the utility functions estimated in this case may differ from the more general ones in equation 4.

There is an alternative, more psychological, explanation as to why decision weights do not influence loss aversion. This explanation relies on the isolation principle incorporated into OPT. The isolation principle states that similar dimensions may be edited out of a given decision problem when other dimensions are more salient (see also Tversky, 1972). In this case probabilities may simply be edited out of mixed prospects, where the outcome

[3] The decision weights drop out of the equation only if either 50-50 odds are employed in the elicitation, or more generally, if the probabilities attributed to gains and losses are the same. Our elicitation procedure as well as most of the existing literature employs 50-50 odds when presenting subjects with mixed gambles. If mixed prospects with different probabilities are used, the decision weights will not cancel each other out. This case may then be more similar to the one of CPT examined above, though it falls outside of the scope of our current study.

dimension is particularly salient. This could also account for other violations of CPT, which appear to be driven by reduced probability distortion in the mixed prospect for moderate, symmetric gain and loss probabilities (Baltussen et al., 2006). We will refer to the resulting definition of loss aversion as *OPT edited*. Using the isolation principle we can obtain (6) even when decision weights are allowed to differ between the gain and loss domains, $\pi^+ \neq \pi^-$, i.e. the change now only takes effect for the mixed decision domain, while choices in the pure decision domain are still as described in equation (1). Importantly, OPT does not explicitly discriminate between these different possibilities.

Whilst the two explanations above give rise to seemingly equivalent definitions of loss aversion, they may have quite different implications for the loss aversion parameter estimated. This is due to the different modelling assumptions underlying the estimation of the utility functions in the gain and loss domains, as represented in equation (1). If the true underlying decision weights are different for gains and losses, constraining $\pi^+ \equiv \pi^-$ in the estimation will affect the estimated utility parameters for gains and losses. This would lead to a different estimate of loss aversion than an unconstrained model with $\pi^+ \neq \pi^-$, where probabilities are simply edited out of the 50-50 mixed prospect decision. Whether this difference is indeed relevant in a given application is an empirical question, which will be addressed below.[4]

Definitions of loss aversion: Expected utility theory

Although loss aversion has come to be understood as an integral part of prospect theory, it was originally proposed by Markowitz (1952) in the context of a reference-dependent expected utility model. Whilst it is tempting to assume that the definitions of loss aversion discussed so far readily carry across to EUT, this is not the case. The difference lies in how each model treats the probabilities. Utility curvature will differ between prospect theory based models that allow for subjectively distorted decision weights and EUT models that assume linear, objective probabilities (Abdellaoui et al., 2007; Bleichrodt et al., 2007; Booij et al., 2010). This follows from the observation that under EUT utility curvature encompasses risk preferences completely, whereas under prospect theory utility

[4] We have listed the 'edited' version as a sub case of OPT because it results in a utility ratio definition. One could equally well consider it a sub case of CPT, where the decision weights are allowed to differ between gains and losses. The crucial difference is not whether probabilities are edited out or decision weights drop out of the loss aversion parameter, but whether decision weights for gains and losses are constrained to be the same.

curvature cannot be automatically equated with risk preferences (Schmidt and Zank, 2008). Under EUT we can use the same indifference condition as before to compute the loss aversion parameter as:

$$\lambda_{\text{EUT}} = \frac{\tilde{v}(x)}{\tilde{v}(\ell)} \tag{7}$$

where the 'tilde' notation again serves to remind us that the utility function used here is not generally the same as the ones seen above. The probabilities now 'drop out' of the definition because loss aversion is elicited from a 50-50 prospect.

Additional restrictions are often imposed on EUT models in empirical analysis. For instance, von Gaudecker et al. (2011) and Andersson, Holm, Tyran and Wengström (2015) assumed equality of utility curvature over gains and losses. Estimation of the common utility curvature parameter in these studies is based on data for gains and mixed prospects only, with no data gathered for prospects involving pure losses (see e.g. Tanaka, Camerer and Nguyen, 2010, for a similar restriction imposed on a prospect theory model). Concavity for gains will automatically translate into convexity for losses under such a restriction. This may be problematic inasmuch as evidence for the latter is much less uniform than for the former (Abdellaoui, 2000; Abdellaoui et al., 2007; Booij et al., 2010). It has also been found that risk seeking for losses may be less stable than risk aversion for gains (Kocher, Pahlke and Trautmann, 2013). Since our data feature prospects with both pure gains and pure losses, we are in a position to trace out the effect this assumption has on estimating loss aversion. We will refer to this model with restricted utility coefficients and the resulting loss aversion as *EUT restricted* for short.

'Behavioural' loss aversion

Finally, we introduce a behavioural definition of loss aversion. We call this definition 'behavioural' inasmuch as it purely reflects behaviour in the mixed prospect, without the need to assume gain-loss separability. As such, it captures loss aversion as a property of behaviour rather than the attribute of any given model or theory. The definition simply takes the following form:

$$\lambda_{Beh} = \frac{x}{\ell} \tag{8}$$

The main drawback is that this definition captures general risk preferences in the mixed prospect, without any possibility to clearly distinguish its constituent parts. In this sense, it is similar to measures developed to capture loss aversion non-parametrically and used mostly in the experimental finance literature (Gneezy and Potters, 1997; Pollmann, Potters and Trautmann, 2014; Sutter, 2007).[5] It has also been adopted in some empirical studies because of its tractability (e.g. Gächter et al., 2010). The measure has the advantage that it is not influenced by any modelling assumptions of the structural model itself, and purely reflects behaviour in the mixed prospect. This makes it a useful benchmark against which to measure the effects of the other definitions. Notice also how it may not be utterly unrealistic to impose the underlying simplifications. We have discussed above that probabilities are likely to drop out of the equation. At that point, all we need to justify this definition is linear utility. While we will see below that utilities are not generally linear in our data, this simplification does away with the necessity to settle on one 'true' utility measure amongst the different ones used. Linear utility over gains and losses also captures the observation that for small stakes most of observed risk aversion must be driven by loss aversion (Rabin, 2000). Finally, it is plausible that outcomes are treated differently in mixed prospects than they are in pure gain or loss prospects, for instance because of the salience of the tradeoff, in which people may focus on the relative outcome amounts for gains and losses rather than on subjective transformations as for gains and losses in their pure form. Conveniently, this definition can be combined with any type of structural model over gains and losses, since estimations in the pure outcome domains do not affect the estimated parameter.

Summary of alternative definitions of loss aversion

Table 1 summarises our six alternative definitions of loss aversion as well as the behavioural definition, and highlights the key differences between them. In addition to showing the general definitions, the table shows whether restrictions are imposed on the whole model, and whether restrictions are imposed only on the mixed prospect. The CPT definition results in the most complete model, so that other definitions can be

[5]These tasks offer the possibility to invest an endowment into a risky project. In case the project is succesful, the invested amount will be multiplied by a given factor, and else the investment is lost. The investment project generally has a positive expected value. One can then take the part of the endowment not invested as an indicator of loss aversion, although just as our behavioural measure it will not allow for the identification of different underlying parameters influencing the choice.

Table 1: Alternative Definitions of Loss Aversion

	Definition	Restrictions whole model	Restrictions mixed
Cumulative Prospect Theory			
λ_{CPT}	$\frac{\pi^+ v(x)}{\pi^- v(\ell)}$	✗	✗
λ_{LU}	$\frac{\hat{\pi}^+ x}{\hat{\pi}^- \ell}$	$v(x) \equiv x$	✗
Original Prospect Theory			
$\lambda_{\text{OPT, equal weights}}$	$\frac{\check{v}(x)}{\check{v}(\ell)}$	$\pi^+ \equiv \pi^-$	✗
$\lambda_{\text{OPT, edited}}$	$\frac{v(x)}{v(\ell)}$	✗	$\pi^j \equiv p$
Expected Utility Theory			
λ_{EUT}	$\frac{\tilde{v}(x)}{\tilde{v}(\ell)}$	$\pi \equiv p$	✗
$\lambda_{\text{EUT,r}}$	$\frac{\tilde{v}_r(x)}{\tilde{v}_r(\ell)}$	$\pi \equiv p$	$\mu \equiv \nu *$
Behavioural			
λ_{Beh}	$\frac{x}{\ell}$	✗	$\pi^j \equiv p$, $u(x) \equiv x$

$*$ Estimated on gain and mixed prospects only

seen as simplifications relative to that model. The behavioural definition is the most restrictive modelling choice imposing that both outcomes and probabilities be treated linearly. The restricted EUT definition lists equality of utility curvature for gains and losses as a restriction on the mixed domain, since we only use gain and mixed prospects to estimate it.[6] Finally, OPT definitions serve as a 'middle ground.' OPT measures estimate subjective decision weights but define loss aversion using only the utility ratio.

3 Experimental design

Participants

A total of 2939 subjects participated in controlled experimental sessions located across 30 countries. Student subjects were used to maintain comparability with typical results from experiments in the Western countries, and because they were deemed more suitable for cross country comparisons than other population groups due to the increased homogeneity of the subject pool. Using students has the further advantage of reducing potential cognitive problems when it comes to understanding abstract decision tasks. Subjects were recruited at major public universities in most country, and at private

[6] Obviously we could use data for both gains and losses to estimate the parameter and just impose equality in curvature for gains and losses. Using only data for gains and the mixed prospect is, however, closer to previous implementations in the literature.

universities in Brazil, Malaysia, Saudi Arabia, and Tunisia.

Care was taken to recruit a subject sample that was balanced in terms of sex and study major, although this was not always completely successful. For example, only males participated in the sessions held in Saudi Arabia because the male collaborator was not allowed to interact with female students. In universities with an existing subject pool we only recruited subjects who had participated in at most 2 previous experiments. This was to ensure similarity to subjects in developing countries for whom experiments were new. A table presenting an overview of the main subject characteristics by country can be found in appendix C.

Experimental task

We elicited certainty equivalents for a total of 44 binary prospects which differed by outcomes, probabilities, decision domain (gains versus losses) and source of uncertainty (known versus vague probabilities). Our analysis excludes the tasks involving unknown probabilities, which are uninformative for studying loss aversion. We further restrict our attention to prospects offering 50-50 probabilities. Because the mixed prospect used to elicit loss aversion offers equal probabilities for the gain and loss, 50-50 prospects are most relevant to our analysis. Focussing only on 50-50 prospects has the advantage that we only need to estimate a decision weight for $p = 0.5$ in the prospect theory formulations instead of the entire probability weighting function. While estimating complete probability weighting functions is more common in the literature, this requires additional assumptions on the functional form of such weighting functions.

Table 2: Experimental tasks

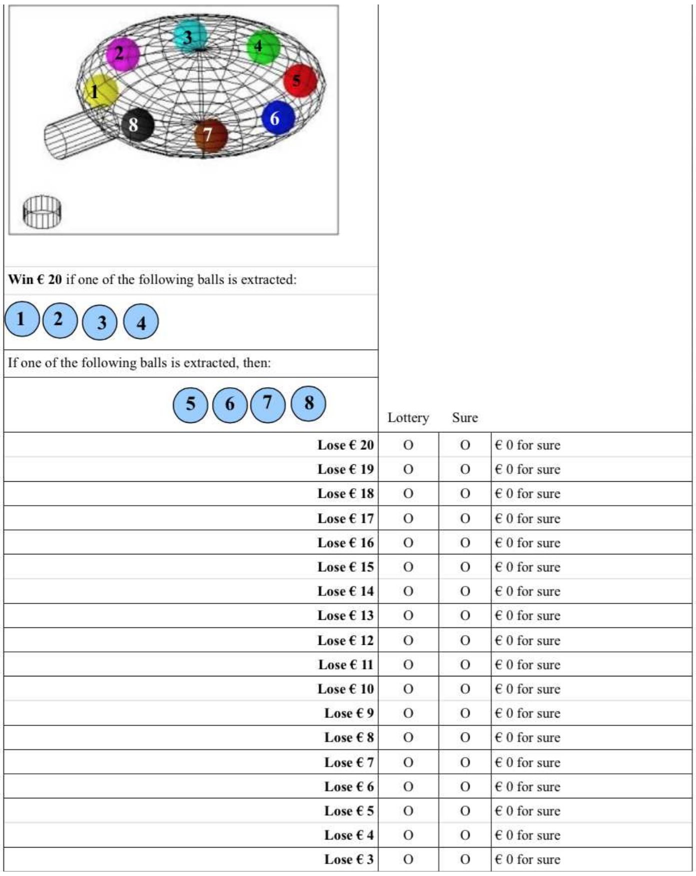
gains	losses	mixed
(5 , 0)	(-5 , 0)	(20 , $-\ell$)
(10 , 0)	(-10 , 0)	
(20 , 0)	(-20 , 0)	
(30 , 0)	(-20 , -5)	
(30 , 10)	(-20 , -10)	
(30 , 20)		

Amounts refer to PPP Euros; €1 = \$1.2 PPP

The tasks included in our analysis are shown in Table 2, with prospects indicated in the form (x, y). There were six elicitation tasks for gains and five for losses. The variation of both higher and lower amounts in the prospects allows us to econometrically separate decision weights from utility curvature. Losses were implemented from an endowment equal to the largest possible loss given to subjects conditional on playing out a lottery involving losses. The outcome range was smaller for losses to limit the costs of the experiment. The tasks were administered in a fixed order, with tasks involving gains administered before losses. The mixed prospect was presented at the end of the section on losses. A large-scale pilot with 330 subjects in Vietnam showed that such a fixed ordering helped to reduce noise and made the tasks easier for subjects, but that it did not affect preferences. It also facilitated the logistics of executing the same experiment in 30 countries using pencil and paper (electricity supply could not be guaranteed at all universities where the experiment was executed, which excluded computerising it).

Tasks over pure gains and pure losses involved choices between a lottery and sure amounts that ranged from the lowest to the highest amount in the prospect. For the mixed prospect we elicited the loss amount ℓ that made a decision maker indifferent between the prospect and the status quo of zero. The mixed prospect is displayed in Figure 1. Subjects were asked to decide between the status quo and a lottery offering a gain of €20, conditional on a ball with the numbers 1-4 being extracted, and a sequence of losses ranging from €-20 to -3, conditional on a ball with the numbers 5-8 being extracted. All subjects were given an endowment equivalent to the highest possible loss conditional on playing the loss part—the only ethically possible course of action in an experiment involving losses. The point where a subject switched from preferring the status quo to preferring the prospect was encoded as the loss equivalent ℓ. Because there is interval in which this equivalent may fall, we approximate the exact amount by the mean between the last loss for which a subject preferred the status quo and the first for which a subject preferred the lottery.

Choice tasks for gains and losses were similar to the mixed prospect, except that the lottery amounts were fixed and the sure amount varied. The sure amount was always bounded by the minimum and the maximum amount offered in the prospect. No tasks were played out for payment until the end of the experiment. At the conclusion of a session, either the gain or the loss part were randomly selected for real play. Then one of the tasks within the selected part was randomly selected. Each task had an equal probability of being selected. For the selected task, one of the lines was then selected at random and played out to determine a subject's payment. All of these task selection procedures were performed transparently in front of subjects, for each subject



Win € 20 if one of the following balls is extracted:

1 2 3 4

If one of the following balls is extracted, then:

5 6 7 8

5 6 7 8	Lottery	Sure	
Lose € 20	O	O	€ 0 for sure
Lose € 19	O	O	€ 0 for sure
Lose € 18	O	O	€ 0 for sure
Lose € 17	O	O	€ 0 for sure
Lose € 16	O	O	€ 0 for sure
Lose € 15	O	O	€ 0 for sure
Lose € 14	O	O	€ 0 for sure
Lose € 13	O	O	€ 0 for sure
Lose € 12	O	O	€ 0 for sure
Lose € 11	O	O	€ 0 for sure
Lose € 10	O	O	€ 0 for sure
Lose € 9	O	O	€ 0 for sure
Lose € 8	O	O	€ 0 for sure
Lose € 7	O	O	€ 0 for sure
Lose € 6	O	O	€ 0 for sure
Lose € 5	O	O	€ 0 for sure
Lose € 4	O	O	€ 0 for sure
Lose € 3	O	O	€ 0 for sure

Figure 1: Elicitation of loss equivalent

individually and in private. After a lottery was played out subjects had the opportunity to verify the compositions of the chance devices. The full instructions can be found in the supplementary materials.

Procedures

All experiments were run between September 2011 and October 2012. We kept the experiments as comparable as possible across countries. Each session was conducted in the teaching language of the university because many countries included in the study have students from multi-lingual backgrounds. The official teaching language is the one common to all students. Instructions were translated from English and back-translated into English by a different person (Brislin, 1970). Differences were then eliminated by discussion.

The payoffs were carefully converted using World Bank PPP data and then double checked using PPP conversion rates calculated from net wages of student assistants at the university where the experiments took place. Vieider (2012) tested explicitly whether small variations in payoffs in the order of $\pm 20\%$ would make a difference in terms of measured risk attitudes and found no effect. The experiment was run in two different cities in China—Beijing and Shanghai—and on two different campuses in Addis Ababa, Ethiopia, to determine whether differences found could be ascribed to variations in the subject pool. Any such differences would be troubling for international comparisons. No differences were found once observable subject characteristics had been controlled for—for details on the results see Vieider, Chmura, Fisher, Kusakawa, Martinsson, Mattison Thompson and Sunday (2015b).

4 Stochastic model and econometrics

The decision making model in Section 2 is deterministic in nature. We now add an explicit stochastic structure to take account of noise in the data. We proceed in two steps. First we use our model's structure to express elicited loss- and certainty-equivalents in terms of model primitives. We then add a decision-specific error, a so-called Fechner error (Hey and Orme, 1994), to observed choices to allow for stochastic elements in decision making. Assumptions on the distribution of the Fechner error give rise to a likelihood function that we use to estimate model parameters.

We define a mixed prospect as $\xi = (x, p; \ell)$, with $x > 0 > \ell$. Because our experiment design elicits ℓ in such a way as to make the decision maker indifferent between playing the prospect and the status quo we can define the modelled loss-equivalent, $\hat{\ell}$, as:

$$\hat{\ell} = v^{-1}\left[\frac{\pi^{+}v(x)}{\lambda\pi^{-}}\right] \tag{9}$$

For a prospect involving pure gains or losses, $\xi_i = (x_i, p; y_i)$ with $|x_i| > |y_i| \geq 0$, we can similarly represent the modelled certainty equivalent $\hat{ce}_i$ as:

$$\hat{ce}_i = v^{-1}\left[\pi^{j}v(x_i) + (1-\pi^{j})v(y_i)\right] \tag{10}$$

The modelled loss equivalents $\hat{\ell}$ in equation (9) and the modelled certainty equivalents $\hat{ce}_i$ in equation (10) depend on the preference parameters $\{\mu, \nu, \pi^{j}, \lambda\}$, or a subset thereof (depending on the restriction imposed in the specific model estimated).

The values predicted based on the model as shown above may differ from observed responses of subjects. Sources of idiosyncratic disturbance may include mistakes in utility calculation by subjects, errors in recording the answers, or noise deriving from the misspecification of the model relative to the true underlying decision process generating the data (Train, 2009). We thus assume that the observed loss equivalent ℓ is equal to the modelled loss equivalent plus some independently distributed error, $\ell = \hat{\ell} + \epsilon$. Equivalently, we assume the observed certainty equivalent ce_i is equal to the predicted certainty equivalent based on the model plus an independently distributed idiosyncratic error, $ce_i = \hat{ce}_i + \epsilon_i$. We assume this error to be mean zero and normally distributed, $\epsilon_i \sim \mathcal{N}(0, \sigma_i^2)$.

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 assume that the error parameter for gains is equal to the error parameter for losses 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 $\sigma_{ji} = \sigma_j |x_i - y_i|$. This takes account of choice lists differing in length, which may have influenced error propensity. For the mixed prospects, the error term depends on the maximum range in the loss domain. Finally, we let σ depend on the observable characteristics of the decision maker, n.

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

$$\psi(\theta_n, \xi_i) = \frac{1}{\sigma_{nij}} \, \phi \left(\frac{\hat{\ell}_{ni}(\theta_n) - \ell_{ni}}{\sigma_{nij}} \right) \tag{11}$$

where ϕ is the standard normal density function, and $\theta_n = \{\mu_n, \nu_n, \pi_n^j, \lambda_n, \sigma_n, \omega\}$ indicates the vector of individual parameters. The $j = -$ index is omitted from the parameter σ_n for notational convenience. For pure gain prospects and pure loss prospects, $\hat{\ell}_n$ and ℓ_n have to be replaced by $\hat{ce}_{ni}$ and ce_{ni} respectively in equation (11).

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

$$L_n(\theta_n) = \prod_i \psi(\theta_n, \xi_i) \tag{12}$$

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, since our main focus is on the error for losses and mixed prospects (results are unaffected if we drop this simplifying assumption). Taking logs and summing over individuals, we obtain the following log-likelihood function:

$$LL(\theta_k, \gamma) = \sum_{n=1}^{N} \log \left[L_n(\theta_n) \right] \tag{13}$$

We estimate this function in Stata 13 (the programs can be downloaded at *removed for anonymous refereeing*). Errors are always clustered at the subject level.

5 Results

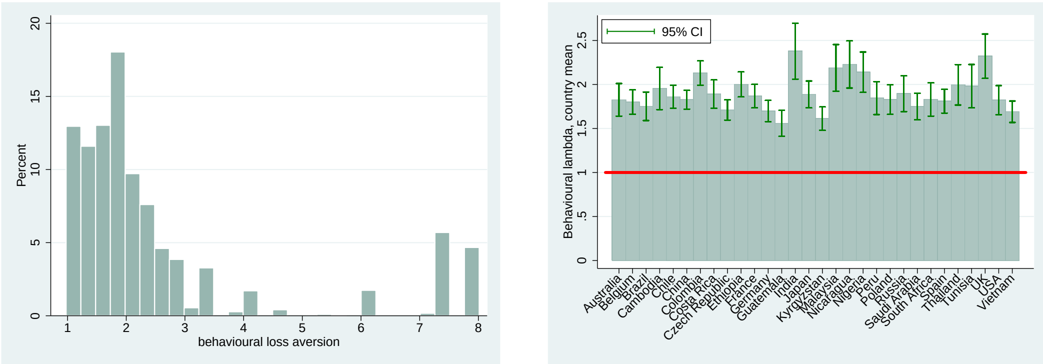
We present the results in five parts. We start by presenting non-parametric descriptives of decisions in the mixed prospect, and by estimating average loss aversion for the different models using all data. Part 2 examines correlations between the behavioural measure and the other six measures, discussing commonalities as well as differences. Part 3 investigates the influence of the different elements contributing to the loss aversion parameters under the different definitions. Finally, we examining the correlates of loss aversion, with part 4 looking at between-country correlates, and part 5 at individual correlates.

5.1 Aggregate results

Figure 2 shows some descriptives to gain a first impression of the data.[7] Figure 2(a) shows the overall distribution of behavioural loss aversion coefficients estimated at the individual level (see supplementary materials for equivalent graphs country by country). The modal response falls close to but just below 2, indicating that around 18% of subjects start accepting the prospect for losses about half the size of the gain. The median parameter is 1.86, while the mean is 2.60. About 13% are close to loss neutral, with values of, or close to, 1. Only relatively few subjects exhibit loss aversion over 3. The

[7]Since the behavioural definition is not affected by estimates over gain and loss prospects, it is immaterial within which model these estimates are obtained. The standard erors may, however, be affected one common standard error is estimated for losses and mixed prospects. We estimated the parameters reported here together with a fully flexible CPT model over gains and losses. The estimation did not converge for two individuals.

exception to this rule are two peaks between 7 and 8, indicating either subjects who never accept the mixed prospect for any loss, or subjects who do so only once the potential loss has become very small.



(a) Distribution of responses

(b) Behavioural lambda by country

Figure 2: Behavioural loss aversion

Figure 2(b) shows the behavioural loss aversion coefficient estimated at the country level, including its 95% confidence interval. All countries show clear risk aversion over mixed gain-loss prospects, with all values significantly above 1. The large majority of countries exhibit a coefficient between 1.5 and 2, which is thus somewhat lower than the canonical 2.25. The only countries with coefficients significantly larger than 2 are India and the UK, with Colombia also coming close. This result differs notably from the effects observed for gains, where risk aversion for the gain part of the prospect $(20, 0.5; 0)$ is rather weak, with some countries risk neutral on average, and some even risk seeking (risk premia are displayed in appendix A). This difference is consistent with the observation that most of the risk aversion in small stake decisions is due to loss aversion (Köbberling and Wakker, 2005; Rabin, 2000). Risk preferences over gains and losses are also more varied than in the mixed domain, with both risk seeking and risk aversion occurring for both gains and losses. This will indeed be helpful in identifying the influence of utility curvature for gains and losses on loss aversion under various modelling assumptions.

We next show some baseline estimates of the loss aversion parameter based on all data, aggregated over individuals and countries. This serves to give us a first idea of whether and how estimates will differ according to the definition used. Table 3 shows the estimated loss aversion coefficients, together with their 95% confidence intervals.

The estimated loss aversion parameter differs considerably across definitions. The

Table 3: Aggregate estimates of the different models

	behavioural	CPT	LU	OPT equal weights	OPT edited	EUT	EUT restr.*
λ	1.892	1.657	1.943	1.781	1.492	1.840	1.803
95% CI	[1.859 1.924]	[1.610 1.704]	[1.896 1.990]	[1.726 1.836]	[1.440 1.545]	[1.780 1.901]	[1.769 1.836]
Observations	35,239	35,239	35,239	35,239	35,239	35,239	20,566
Subjects (clusters)	2939	2939	2939	2939	2939	2939	2939
LL	-87,624	-87,624	-87,842	-87,664	-87,624	-87,746	-53,633

* estimated using only gains and the mixed prospect

behavioural definition results in an estimate around 1.9, which is close to but significantly smaller than 2. More importantly than the actual values in this first step, however, are the differences between the definitions. Indeed, all the estimates appear to be significantly different from the behavioural estimate, with the EUT definition coming closest. Most definitions also result in estimates that are significantly different from those obtained under all other definitions. The OPT definition with edited-out probabilities results in a particularly low estimate, followed by the CPT definition. The OPT equal weights definition produces an estimate that is significantly higher than the one of the OPT edited model, and that falls between the one for CPT and the EUT models (although it is significantly different from both). The two EUT formulations produce estimates that are relatively close to each other.

5.2 Country-level correlations between estimates

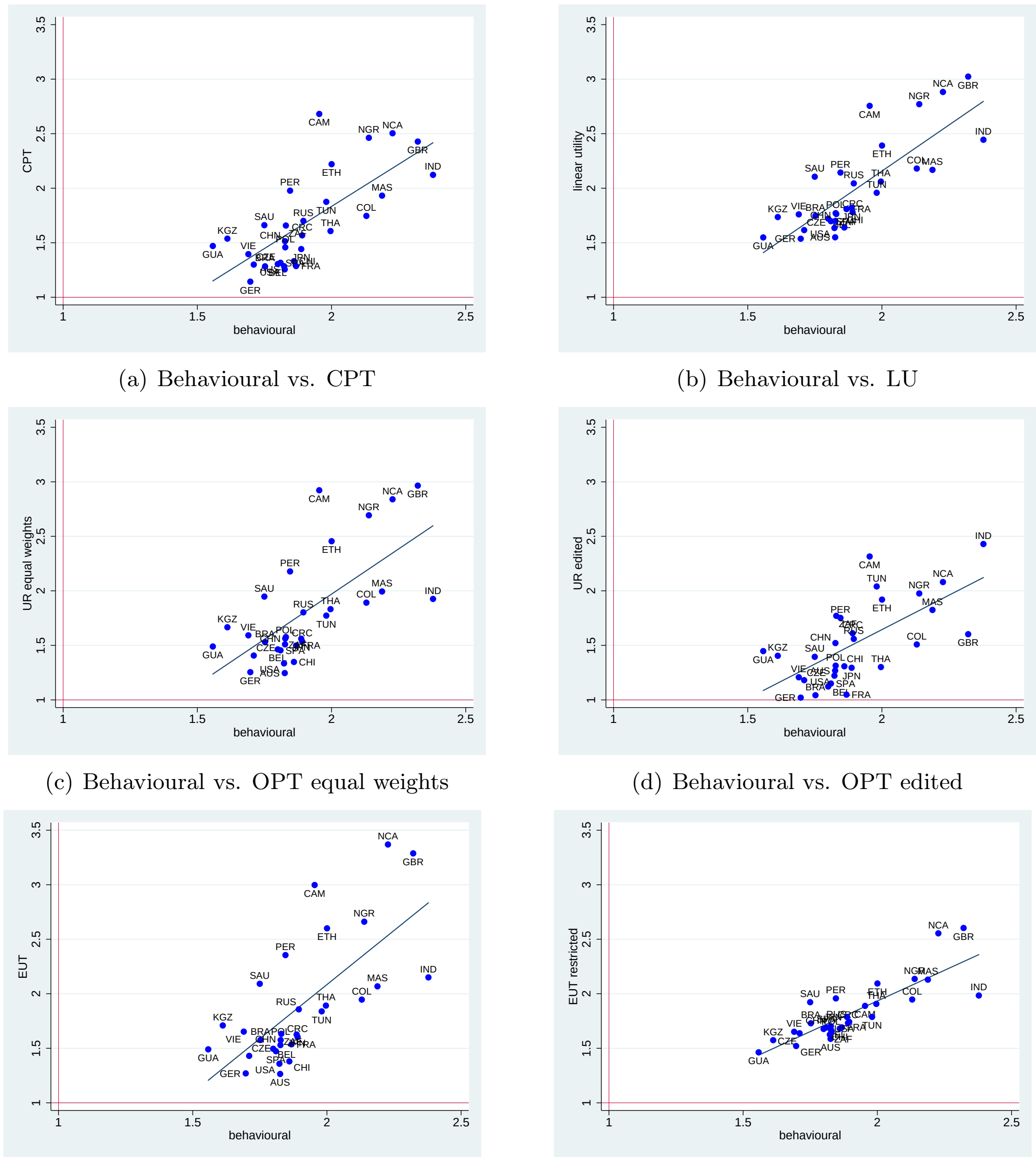
We now estimate the different models country by country. To the extent that utility parameters and decision weights will be different across countries, this may indeed influence our loss aversion estimates to differing degrees, depending on the extent to which these different parameters play a role. Estimating loss aversion at the country level has the advantage that the estimates are stable and extreme behaviour by some individuals does not unduly distort them. While the composition of our subject pool differs somewhat between countries, this is only of secondary importance. Indeed, the purpose of the present section is to establish how the estimated parameters vary across models. The issue of individual as well as country-level correlates will be addressed below. A full estimation table detailing differences across all 30 countries is reported in appendix B. Here we concentrate on painting a picture of the general trends in the data.

Figure 3 shows a series of scatter plots between the behavioural definition of loss aversion and the other six definitions. We find large differences between definitions across countries. Figures 3(a) and 3(b) plot behavioural loss aversion against the CPT definition and the CPT definition assuming linear utility. The coefficients under the different definitions show a high correlation ($\rho = 0.730$ for CPT and $\rho = 0.827$ for linear utility; Spearman rank correlation). Nonetheless, several differences stand out. As already seen above, the behavioural definition shows a relatively low dispersion, with all countries estimated to have a loss aversion parameter between 1.5 and 2.4. In contrast to this, the CPT parameters are shifted downward on average by about 0.5., meaning that some countries such as Germany show very little loss aversion at all. This is consistent with previous studies finding relatively low loss aversion employing the CPT definition (e.g., Booij et al., 2010; Harrison and Rutström, 2009).[8] We also find a higher dispersion of the parameters under CPT. The linear utility coefficients are not quite as low as the ones estimated under CPT, but reach higher values than either the behavioural coefficients or the CPT coefficients.

The loss aversion coefficients estimated under OPT equal weights and OPT edited are plotted against behavioural loss aversion in figures 3(c) and 3(d) respectively. Once again, they show a high correlation with behavioural loss aversion ($\rho = 0.670$ for the equal weights version, and $\rho = 0.692$ for the edited version), although not quite as high as the CPT variants shown above. The equal weights definition shows wider dispersion than any of the measures discussed so far, ranging from about 1.25 up to 3. This likely derives from higher heterogeneity in utility estimates, which under the equal weights assumption capture all the differences between gains and losses (we will further discuss this below). For the OPT edited definition we find lower dispersion. In addition, we find all estimates to be shifted downwards relative to OPT equal weights. Some countries such as Germany, Belgium, and France have loss aversion coefficients extremely close to and not significantly different from 1 according to this definition, so that we would actually need to speak of loss neutrality for those countries. According to the behavioural definition, on the other hand, these countries remain clearly loss averse, with coefficients between 1.7 and 1.9. This also goes to show that the ordering of countries in terms of loss aversion is affected by the type of definition we adopt.

Finally, figure 3(e) shows the scatter plot of the behavioural loss aversion coefficient against the EUT estimates ($\rho = 0.683$), and figure 3(f) plots behavioural loss aversion against the restricted EUT estimates ($\rho = 0.849$). The EUT model results in the highest

[8]Direct comparisons are difficult to carry out, since other studies also differ from ours along a number of important dimensions that are not varied here, such as experimental tasks and functional forms. Any comparison thus needs to be treated with caution, and we will thus avoid them henceforth.



(a) Behavioural vs. CPT (b) Behavioural vs. LU

(c) Behavioural vs. OPT equal weights (d) Behavioural vs. OPT edited

(e) Behavioural vs. EUT (f) Behavioural vs. EUT restricted

Figure 3: Scatter plots of behavioural loss aversion against other definitions

spread we have seen—with parameters ranging between about 1.25 and almost 3.5. This shows the full effect of risk attitudes for gains and losses being estimated into the domain-specific utility functions, and then used to adjust the loss aversion coefficient. The restricted EUT estimates, on the other hand, fall into a range very similar to the one observed for the behavioural measure. They also exhibit the highest correlation with the behavioural estimates across the six measures examined (although this is closely followed by CPT with linear utility).

It is particularly instructive to look at some pairs of countries that have about the same loss aversion according to the behavioural definition, i.e. in which the average switching point in the mixed gain-loss task coincides. Examples of such country pairs are Germany and Vietnam, and Thailand and Ethiopia. Germany is invariably amongst the countries with the lowest loss aversion, and this seems to a large extend driven by highly concave utility for both gains and losses, resulting in a very high utility ratio. Vietnam, for which we cannot reject the hypothesis that the average switching point is the same as Germany in the mixed prospect ($z = 0.499, p = 0.618$, Mann-Whitney test), is estimated to have higher loss aversion in all the models displayed. This difference appears smallest in the restricted EUT formulation, with the same curvature parameter applied to gains and losses, and is highest in models such as EUT and OPT edited. The same tendency is visible for Thailand and Ethiopia. Although we again cannot reject equality of switching points ($z = 0.575, p = 0.565$), if anything the differences are even larger than for Vietnam and Germany, which seems largely due to the high degrees of risk seeking for gains observed in Ethiopia. This provides a first indication of the influence parameters estimated over pure gains and losses have on estimated loss aversion. We will now proceed to investigating this issue more systematically.

5.3 Determinants of loss aversion coefficients

In this section we look into the determinants of loss aversion estimates across the various definitions. We start by showing the correlations between the various loss aversion estimates and the ratio of utility functions (and/or decision weights) estimated for pure gain and loss prospects. These ratios differ significantly across the different models in all possible pairs between models for which a utility ratio can be meaningfully defined, showing that using different utility symbols across models was indeed justified.[9] Utility estimates for gains under CPT range from clearly concave at 0.058 to linear at 0.008, with a median of 0.035. For losses, the parameters range from strong convexity (0.144) to significant concavity (-0.022), with a median parameter close to linearity at 0.004. Under EUT, we estimate utility curvature parameters for gains ranging from clear concavity at 0.034, to clear convexity at -0.024 (although the median country has concave

[9] We cannot reject the hypothesis that the utility ratio in the EUT model and the weights ratio in the linear utility model are the same. The two also show an extremely high correlation at $\rho = -0.976$. This is indeed logical, seen that these two models are the dual of each other.

utility at 0.016).[10] For losses, the picture is similar, with estimates ranging from strong convexity at 0.107, to concavity at -0.014, and a median close to linearity at 0.008.

Relating the estimated loss aversion parameters to its constituent parts will allow us to assess the degree to which preference parameters estimated from equation (1) in the pure gain and loss domains influence the estimated loss aversion parameters under the different models. We can then compare these estimates to a correlation analysis of the behavioural measure with the same parameters estimated over pure gains and losses. While the former shows the degree to which the utility and/or weight measures estimated for pure gains and losses impact the estimated loss aversion coefficient once gain-loss separability is imposed, the correlation between the same utility parameters and the behavioural loss aversion measure ought to give us an indication of the empirical and behavioural import of the same measures. That is, the extent (if any) to which the correlation for the behavioural measure falls short of the correlation obtained once gain-loss separability is imposed ought to give us an—albeit indirect—indication of the behavioural validity of the gain-loss separability assumption. This derives from the simple observation that in the mixed prospect, we elicited the loss amount ℓ in such a way as to equalise the utility of the prospect to the status quo. The elicited measure should thus be influenced by measures of utility estimated under gains and losses if gain-loss separability holds empirically.

Figure 4 plots these relations for the six models in which estimates in the gain and loss domain feed directly into the estimation of loss aversion. We always use ratios of the exponentials of the utility parameters, ${}^{\exp(\mu)}/_{\exp(\nu)}$, so as to avoid negative values that could result from either convex utility for gains or concave utility for losses (we never find a combination of convexity for gains and concavity for losses at the country level). Figure 4(a) shows the correlation of the utility ratio estimated under CPT with the loss aversion parameter estimated under CPT, as well as with the behavioural loss aversion parameter. The correlation with the CPT loss aversion coefficient is strong and highly significant

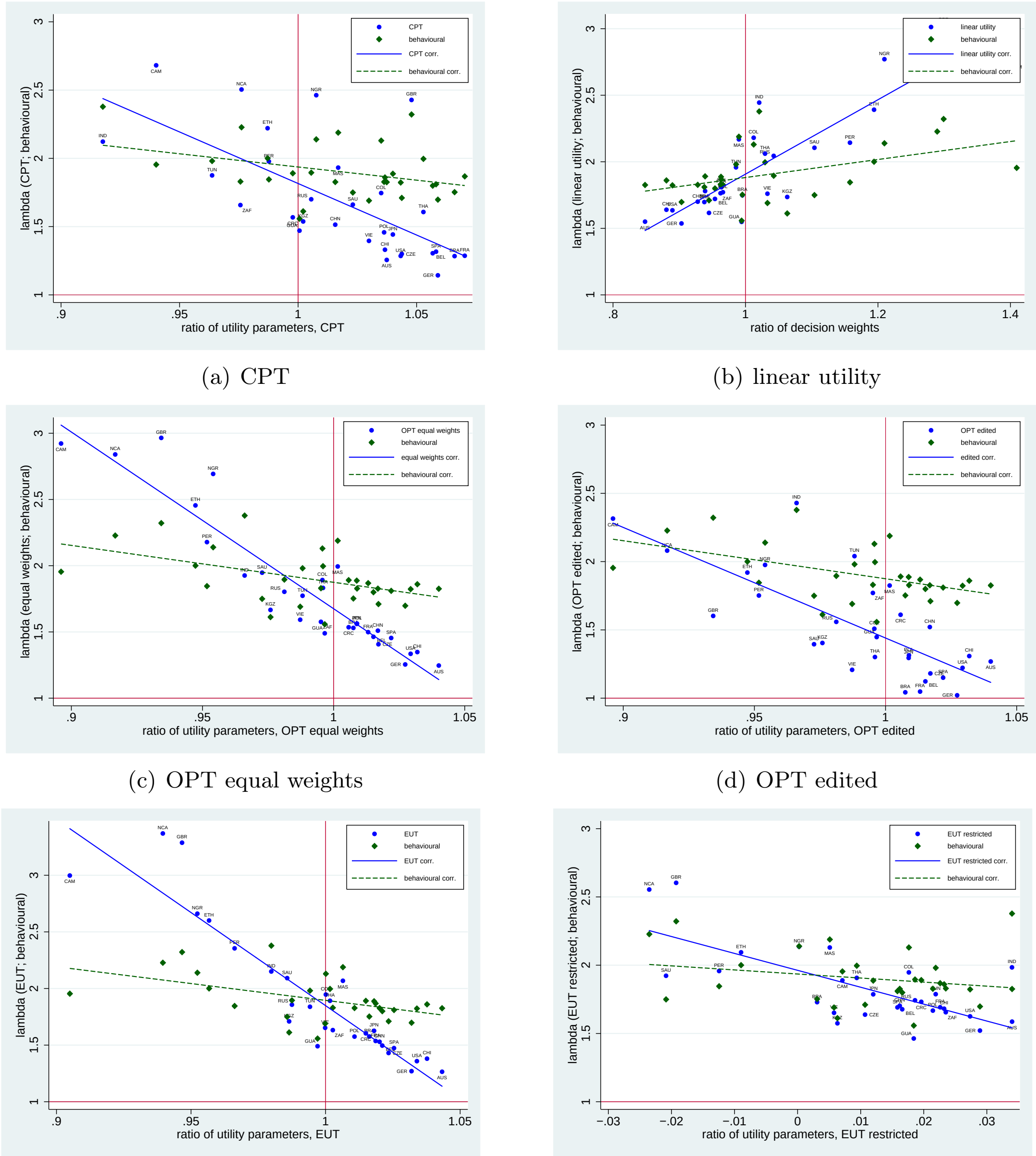
[10] Convex utilities for gains especially may seem unusual. Since we find quite a lot of risk seeking in some countries, however, in the EUT formulaton risk seeking can only be captured in a convex utility function, while it is generally captured in probability weights under more general prospect theory formulations (see also L'Haridon and Vieider, 2015 for the estimation of complete probability weighting functions). Vieider, Beyene, Bluffstone, Dissanayake, Gebreegziabher, Martinsson and Mekonnen (2014) found similar levels of risk seeking with a representative sample of the Ethiopian rural highland population, and discussed EUT versus Dual-EUT to capture this phenomenon. See also Vieider, Truong, Martinsson and Pham Khanh (2013) for a related finding with a farmer sample in Vietnam.

($\rho = -0.729, p < 0.001$). This provides an indication that the utilities estimated over gains and losses have a great impact on the loss aversion coefficient estimated within the model across our 30 countries. The correlation of the CPT utility ratio with the behavioural loss aversion parameter is much weaker, and only marginally significant ($\rho = -0.354, p = 0.055$). This indicates that the imposition of utility curvature estimated for gains and losses on the loss aversion parameter may have a stronger impact on the latter than empirically warranted by behaviour in the mixed domain.[11]

The correlation with the decision weight ratio in the linear utility model, shown in figure 4(b), is positive and also highly significant ($\rho = 0.806, p < 0.001$). The correlation of the same weights ratio with the behavioural loss aversion parameter is, once again, much weaker ($\rho = 0.413, p = 0.023$). Figure 4(c) plots the loss aversion coefficient according to the OPT equal weights definition against the utility ratio in the same model. As we would expect, we again find a clear downward sloping relation with the utility ratio ($\rho = -0.935, p < 0.001$), since more concave utility of gains and/or more convex utility for losses depress the loss aversion parameter. The correlation with behavioural loss aversion is considerably weaker, though still highly significant ($\rho = -0.488, p = 0.006$). Figure 4(d) shows very similar findings for the OPT edited definition. While the correlation with the theoretically correct definition is very strong ($\rho = -0.891, p < 0.001$), the correlation with the behavioural loss aversion index is considerably weaker ($\rho = -0.354, p = 0.055$), and only marginally significant.

We find similar downward slopes in figure 4(e) for EUT ($\rho = -0.929, p < 0.001$), and in figure 4(f), showing the correlation with the utility curvature parameter for gains in the restricted EUT model ($\rho = -0.572, p < 0.001$). The strength of the correlations illustrates just how large an effect the ratio of utilities estimated under gains and losses has for the estimate of the loss aversion parameter as defined under the different models. For behavioural loss aversion, the correlation is again much weaker, at ($\rho = -0.483, p = 0.007$) and ($\rho = -0.148, p = 0.437$) for EUT and EUT restricted respectively. Indeed, for the restricted model there is no significant correlation at all. The strongest correlations with the behavioural loss aversion index were observed for the EUT model and the OPT

[11] Under the CPT defintion, loss aversion is also affected by decision weights. A correlation of the CPT loss aversion parameter with the ratio of the decision weights (not shown) is not significant ($\rho = 0.153, p = 0.420$). The same holds for the correlation of the decision weights ratio with the bahvioural loss aversion parameter ($\rho = 0.483, p = 0.133$). This picture changes, however, when we regress the parameter on both the utility and the weights ratio. In that case, the weights ratio is significant at the 5% level for both loss aversion parameters.



(a) CPT

(b) linear utility

(c) OPT equal weights

(d) OPT edited

(e) EUT

(f) EUT restricted

Figure 4: Scatter plots of loss aversion against utility ratios/weight ratios

model with equal weights for gains and losses. That may not be surprising, as the two models come closest to capturing all (the differences in) risk preferences over gains and losses in the utility parameters.

Yet a different way of approaching the data is to regress the loss aversion parameters on the component parts of their definition, and then examining the variance explained by those components. This ought to give us an indication of the extent to which the between-country variation in loss aversion parameters is driven by between-country difference in

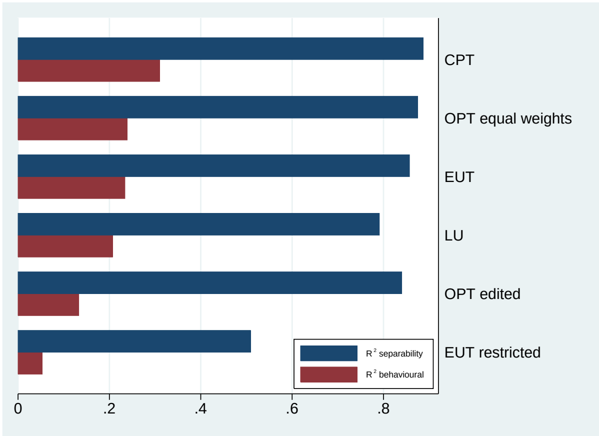


Figure 5: R^2 from regression of loss aversion on the component parts of its definition

risk preferences for gains and losses. Figure 5 depicts the comparative R^2 values when the loss aversion parameter by country is regressed on the utility and/or decision weight ratio. For the measures estimated assuming gain-loss separability, the R^2 ranges from 51% for EUT restricted, to 86% for the OPT definition with equal weights, and fully 89% for loss aversion under CPT regressed on both the utility ratio and weight ratio. Most of the between-country variation in loss aversion can thus be seen to derive from between-country variation in risk aversion for gains and losses. For behavioural loss aversion, the variance explained by the measures over gains and losses is much lower in general, ranging from only 5% in the restricted EUT model to a high of 24% in the OPT equal weights model, and 31% in the CPT model. In other words, there remains much variation in loss aversion across countries that is not explained by variation in risk preferences for gains and losses. We will now proceed to examining potential between-country correlates.

5.4 Between country correlates of loss aversion

We next look at over-reaching trends between countries. This will help us assess to what extent trends between countries, such as the ones reported by L'Haridon and Vieider (2015) based on the linear utility model, are indeed driven by behavioural differences in the mixed domain, or rather reflect the influence of parameters estimated for pure gains and losses. This is important inasmuch as regressions of theoretically correct loss aversion measures may reflect effects on utility rations rather than on behaviour in the mixed domain—a hypothesis made plausible by the large influence of the constituent parts of the definition on estimated parameters just discussed.

Table 4 shows a regression of the different loss aversion parameters on macroeconomic indicators such as GDP per capita (measured as the log difference from the US in PPP for 2011, World Bank Data) and the Gini coefficient as a measure of income inequality (entered as a z-score). We further add other measures from the macroeconomic literature on growth and development. These include the predicted genetic diversity of a country, as well as predicted genetic diversity squared (Ashraf and Galor, 2013), the absolute distance from the equator (in minutes of latitude; Gallup, Sachs and Mellinger, 1999), and continental fixed effects. Finally, the regression controls for a few potential confounding factors at the individual level, such as whether a participant is a foreigner in the country where the experiment takes place, as well whether the experiment was carried out at a private university. We also control for the participant's sex since sex proportions differ between countries, and could otherwise skew our estimates (we will discuss gender effects below).

Table 4: Relationships with between-country indicators depending on definition

dep. var: λ	behavioural	CPT	LU	OPT eq. weights	OPT edited	EUT	EUT restr.
GDP p.c. (diff. from US)	-0.027	0.200***	0.124***	0.219***	0.208***	0.228***	0.008
	(0.034)	(0.048)	(0.047)	(0.056)	(0.065)	(0.061)	(0.033)
predicted genetic div.	-0.066	-0.067	-0.161	-0.168	0.042	-0.152	-0.054
	(0.079)	(0.116)	(0.114)	(0.134)	(0.145)	(0.149)	(0.083)
genetic diversity squared	-0.025	-0.117**	-0.085*	-0.119**	-0.134**	-0.113*	-0.005
	(0.032)	(0.050)	(0.048)	(0.059)	(0.059)	(0.065)	(0.035)
minutes latitude	-0.006***	-0.005**	-0.009***	-0.009***	0.001	-0.010***	-0.008***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)
foreigner	-0.030	-0.047	-0.024	-0.024	-0.103	-0.024	-0.021
	(0.069)	(0.083)	(0.083)	(0.096)	(0.097)	(0.104)	(0.066)
Gini	-0.001	0.017	-0.019	-0.012	0.123**	-0.026	-0.020
	(0.028)	(0.038)	(0.036)	(0.043)	(0.052)	(0.046)	(0.026)
private university	-0.012	0.051	0.030	0.062	0.048	0.091	0.043
	(0.066)	(0.091)	(0.089)	(0.104)	(0.117)	(0.117)	(0.069)
OPEC	-0.016	0.242	0.287*	0.481***	-0.132	0.499**	0.157
	(0.095)	(0.149)	(0.158)	(0.179)	(0.169)	(0.202)	(0.108)
Africa	0.076	0.047	-0.102	-0.154	0.302*	-0.183	-0.041
	(0.096)	(0.124)	(0.122)	(0.140)	(0.157)	(0.152)	(0.089)
Asia	-0.095	-0.260**	-0.379***	-0.465***	-0.062	-0.459***	-0.125
	(0.084)	(0.111)	(0.114)	(0.132)	(0.128)	(0.146)	(0.082)
Americas	-0.196	-0.114	-0.452**	-0.445**	0.238	-0.420*	-0.215
	(0.165)	(0.190)	(0.203)	(0.223)	(0.254)	(0.247)	(0.151)
Oceania	-0.194	-0.255	-0.592***	-0.639***	0.269	-0.656***	-0.318**
	(0.149)	(0.191)	(0.193)	(0.219)	(0.242)	(0.240)	(0.144)
female	✓	✓	✓	✓	✓	✓	✓
constant	2.172***	1.731***	2.356***	2.120***	1.189***	2.188***	2.105***
	(0.107)	(0.149)	(0.150)	(0.177)	(0.202)	(0.194)	(0.108)
Observations	35,239	35,239	35,239	35,239	35,239	35,239	20,566
Subjects (clusters)	2939	2939	2939	2939	2939	2939	2939
LL	$-86,045$	$-86,047$	$-86,347$	$-86,111$	$-86,041$	$-86,221$	$-52,976$

* , ** , *** indicate significance at the 10, 5 and 1 % level respectively
GDP is measured as the log difference of GDP in PPP from the US in 2011; World Bank data
Genetic diversity and the Gini coefficient are entered as z-scores

We find almost no effects for behavioural loss aversion, consistent with the interpretation of loss aversion as an idiosyncratic psychological trait. The one exception to this rule is a strongly significant negative effect of geographical latitude or distance from the equator. This effect is also preserved for all the other definitions except the one of OPT edited. This is a reflection of the fact that latitude has no influence on risk preferences under gains and losses (Vieider et al., 2012), thus not distorting the effect found for behavioural loss aversion in the other models. The effect persist also if continental fixed effects are dropped, a regression we do not show here for parsimony.

On the other hand, we find several effects for other definitions that are not significant for the behavioural definition. These are mostly driven by contrasting effects for gains and losses, which are then fed back into the respective definitions of loss aversion (see supplementary materials for complete regressions including all parameters). This effect is strongest for GDP per capita. Indeed, the difference in GDP per capita from the US shows a significantly positive correlation with almost all definitions of loss aversion but the behavioural one, with EUT restricted the sole exception. This is promptly explained by the strong effects GDP per capita has on the various component parts under the different definitions. For instance, utility for gains becomes generally less concave with poverty (i.e., the parameter decreases), while utility for losses becomes more convex (i.e. the parameter increases). This results in a lower utility ratio, and hence higher estimated levels of loss aversion, in poor countries. The effect, however, derives purely from effects observed in the pure outcome domains for gains and losses, and they do not carry over to behaviour in the mixed domain.[12]

5.5 Effects of individual characteristics

Finally, we examine differences in loss aversion across observable characteristics of subjects. We use physical characteristics, such as sex, age, and physical height or stature, as well as study characteristics, such as grade point average and study major. Table 5 shows the results. We start from gender effects, which are ardently discussed in the literature also with a view of differential job market outcome which may derive in parts from difference in willingness to compete and risk preferences (Balafoutas and Sutter, 2012; Niederle and Vesterlund, 2005; Villeval, 2012). Women haven often been found to be more risk averse than men in the literature (see references inCroson and Gneezy, 2009),

[12]We find similar effects for other measures, such as e.g. genetic distance squared, the Gini coefficient, or the OPEC dummy. We do not discuss these further as they are not the principal interest of the paper. The interested reader can find the reasons underlying these effects in the regression tables reported in the supplementary materials.

although some studies cast doubt on the universality of this finding (Booth and Nolen, 2012; Filippin and Crosetto, 2014). In terms of loss aversion more specifically, the gender effect is even more muted. Some studies find women to be more loss averse than men (see e.g. Andersson et al., 2015; Booij et al., 2010; Brooks and Zank, 2005; Schmidt and Traub, 2002), while others find no gender effect (Gächter et al., 2010; Harrison and Rutström, 2009; Tanaka et al., 2010). Some studies even find women to be less loss averse than men (Holden, 2014).

Table 5: Regression of loss aversion on individual characteristics depending on definition

dep. var: λ	behavioural	CPT	LU	OPT equal weights	OPT edited	EUT	EUT restricted
female	**0.095*** **	-0.065	-0.026	**-0.115** **	0.048	**-0.117** **	0.000
	(0.032)	(0.042)	(0.040)	(0.045)	(0.066)	(0.049)	(0.030)
age	0.007	0.062***	0.023	0.041*	0.096***	0.040	0.003
	(0.020)	(0.023)	(0.023)	(0.025)	(0.035)	(0.026)	(0.017)
height	**-0.039** **	-0.003	-0.009	0.007	-0.018	0.009	-0.028
	(0.020)	(0.025)	(0.025)	(0.027)	(0.044)	(0.029)	(0.019)
GPA	-0.017	-0.077***	-0.054**	-0.077***	-0.065**	-0.085***	-0.025
	(0.020)	(0.023)	(0.024)	(0.026)	(0.032)	(0.029)	(0.018)
math	**-0.106***	-0.069	-0.126*	-0.096	-0.080	-0.115	-0.094*
	(0.055)	(0.068)	(0.065)	(0.074)	(0.118)	(0.081)	(0.052)
natural	-0.060	-0.134	-0.118	-0.148	-0.189	-0.151	-0.073
	(0.073)	(0.085)	(0.085)	(0.093)	(0.143)	(0.099)	(0.064)
medicine	-0.059	-0.070	-0.167*	-0.195*	0.054	-0.189	-0.085
	(0.075)	(0.098)	(0.090)	(0.109)	(0.137)	(0.120)	(0.072)
social science	0.014	-0.039	-0.049	-0.076	0.091	-0.093	-0.061
	(0.058)	(0.071)	(0.074)	(0.083)	(0.115)	(0.089)	(0.055)
humanities	0.045	0.038	-0.009	-0.029	0.104	-0.024	-0.006
	(0.069)	(0.098)	(0.093)	(0.104)	(0.133)	(0.114)	(0.066)
arts	0.049	0.198	0.159	0.194	0.084	0.270	0.128
	(0.119)	(0.154)	(0.168)	(0.176)	(0.224)	(0.223)	(0.136)
study other	-0.005	-0.000	-0.082	-0.080	0.012	-0.084	-0.036
	(0.055)	(0.068)	(0.065)	(0.075)	(0.100)	(0.081)	(0.050)
country dummies	✓	✓	✓	✓	✓	✓	✓
constant	1.817***	1.433***	1.740***	1.531***	1.276***	1.574***	1.704***
	(0.097)	(0.086)	(0.098)	(0.101)	(0.145)	(0.111)	(0.075)
Observations	35,239	35,239	35,239	35,239	35,239	35,239	20,566
Subjects (clusters)	2939	2939	2939	2939	2939	2939	2939
LL	−85,284	−85,286	−85,642	−85,383	−85,284	−85,526	−52,611

* , ** , *** indicate significance at the 10, 5 and 1 % level respectively
age and GPA are entered as z-scores; height is normalized by sex

Our main focus is whether different definitions of loss aversion may produce different results. The effect in this respect is dramatic. Using the behavioural definition, we find women to be more loss averse than men, an effect consistent with the prevalent gender effect found for risk preferences. For OPT equal weights and EUT, on the other hand, we find *women to be significantly less loss averse than men*. The remaining four definitions show no significant gender effects. Depending on what definition one adopts, one may thus conclude that women are more loss averse than men, less loss averse than men, or equally loss averse as men.[13] Once again, to explain these differences we need to look at

[13] The gender dummy is not the only variable for which such effects are found. The country regression

what happens to risk preference for gains and losses. In the models showing the negative effects, women are estimated to be much more risk averse than men for gains. For losses, the effect also goes towards more risk aversion for women, but this effect is much weaker than for gains. This results in higher utility ratios for women, and hence in a decrease in loss aversion when gain-loss separability is imposed. This effect is indeed so strong as to overwhelm the effect in the opposite direction in behavioural terms.

Behavioural loss aversion is also found to decrease in physical stature (an effect that has previously been found for risk in general: Dohmen, Falk, Huffman, Sunde, Schupp and Wagner, 2011; Vieider et al., 2014). This effect does not carry over to any of the other definitions. Behavioural loss aversion is also somewhat lower for students majoring in mathematics or engineering (marginally significant), which carries over to two other definitions. Other notable correlations occur for other definitions while being absent for behavioural loss aversion. Most prominent are the ones with GPA and with age. Both are significant in some specifications, but not in others. In general, we can again think of them as being driven mostly by risk preferences for pure gains and losses, but we do not discuss the drivers in detail here (the full regressions are reported in the supplementary materials).[14]

6 Discussion and conclusion

Loss aversion has been implicitly defined in many different ways in estimations of the parameters of prospect theory and reference-dependent expected utility theory. The estimates obtained across these different modelling assumptions vary widely, and a clear understanding is rendered difficult by the fact that the exact specification underlying loss aversion is often not spelled out explicitly. We showed that different definitions result in very different estimates. First of all, quantitative estimates of loss aversion vary widely depending on the exact modelling assumptions. Estimating loss aversion across 30 countries allowed us to obtain stable estimates not unduly influence by individual outliers, while the large variability of risk preferences for gains and losses allowed us to systematically investigate the effect of imposing utility curvature measured over gains and losses on the loss aversion definition. The effect of such gain-loss separability was

in appendix B shows that Kyrgyzstan is more loss averse than the US according to the behavioural definition, but less so according to CPT and OPT equal weights. It is equally loss averse as the US according to all other definitions.

[14] Other individual characteristics in our data set, such as religion and cultural attitudes as measured by the Hofstede scales, do not add any interesting insights, so that we chose not to report them here.

found to be large, with behavioural loss aversion showing much lower correlations with risk preferences over gains and losses. This in turn means that in regression analysis, between-country and individual characteristics may even show effects *going in opposite directions* for different definitions of loss aversion. We have seen this prominently for gender effects, where we found women to be more loss averse than men according to the behavioural definition, but less loss averse than men according to two other definitions, while finding no difference for the remaining four definitions.

While bringing to bear a host of data on the issue, our analysis was limited in some important ways. For instance, it is not clear what to do in cases where probabilities between gains and losses differ in mixed prospects. One could then still make a point that loss aversion should be incorporated into utility and that decision weights should play no role in the definition (e.g. in order to obtain one unifying concept that can be applied both to risky and riskless choice; see Schmidt and Zank, 2005), but this argument would be purely normative in character rather than founded on empirical psychological arguments as the definitions used above. Also, our argument had a clearly empirical focus on the implications of different modelling assumption. In this sense, it is best seen as complementary to the results obtained by (Abdellaoui et al., 2007). The latter adopted one specific modelling assumption from prospect theory, a model that most closely resembles what we called OPT, and tested different theoretical definitions and their implications for measurements of prospect theory. We furthermore added to this finding by tracing the differences between models back to the constituent parts of the loss aversion definitions under the different models, and by showing the effects of such assumptions in regression analysis.

The crucial point underlying all the differences found is the cross-fertilisation of parameters across domains, and the differences in parameter estimates according to various models. According to a simple behavioural definition, we estimated loss aversion purely based on the loss amount elicited in the mixed prospects to equalise the utility of the gain and loss in that prospect. Clearly, this is not a theoretically pure measure of loss aversion, as it more generally reflects risk preferences in the mixed outcome domain. The alternative is to assume gain-loss separability, and to obtain a theoretically correct measure. To the extent that utilities measured in the pure gain and loss domain may be different from the utilities underlying behaviour in the mixed prospect, imposing these parameters deriving from the estimations in the pure gain and loss domains may however distort loss aversion. This issue is further compounded by the observation that the parameters obtained may depend heavily on the assumptions underlying those estimations. There thus remains the issue of which theory may be the 'correct theory'.

The question then arises what may be the solution to this conundrum. From a theoretical point of view, the difference in utility may be seen as a challenge to the theoretical integrity of prospect theory (see Wu and Markle, 2008, for a related finding). By the same token, it could also be seen as challenge to the integrity of reference-dependent expected utility formulations. From a more practical empirical perspective, the issue is rather what to do about the widely differing estimates obtaining from the different definitions. The solution here may be simply to adopt the behavioural definition of loss aversion in structural estimations. This has a number of advantages: i) it is the purest measure of behaviour in gain-loss prospects, and thus ideally suited for regression analysis and quantification purposes; ii) it can easily be added to any decision model estimated over gains and losses, whatever form the latter may take; and iii) the estimates obtained are completely independent from the decision model adopted, so that estimates obtained are comparable across different models and approaches. We thus think that adding such a measure in addition to one's favourite model-based measure could greatly improve the comparability of loss aversion estimates across studies.

A Relative risk premia for gains and losses

Below we show normalised risk premia for gains $(20, 0.5; 0)$ and losses $(-10, 0.5; 0)$. We use smaller outcomes for losses as the loss in the mixed prospect for which subjects switch is typically about half as large as the gain. The relative risk premium is defined as $\frac{EV-CE}{EV}$, where EV is the expected value of a prospect and CE its certainty equivalent.

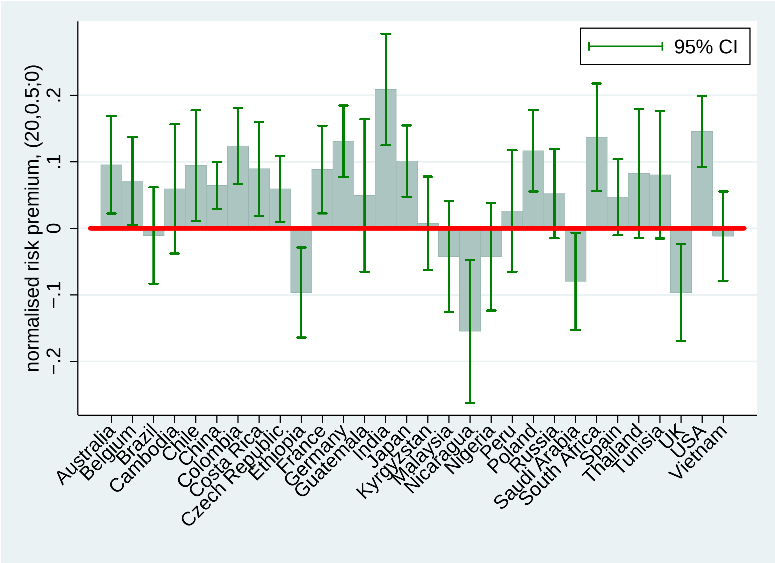


Figure 6: Relative risk premia for (20,0.5;0)

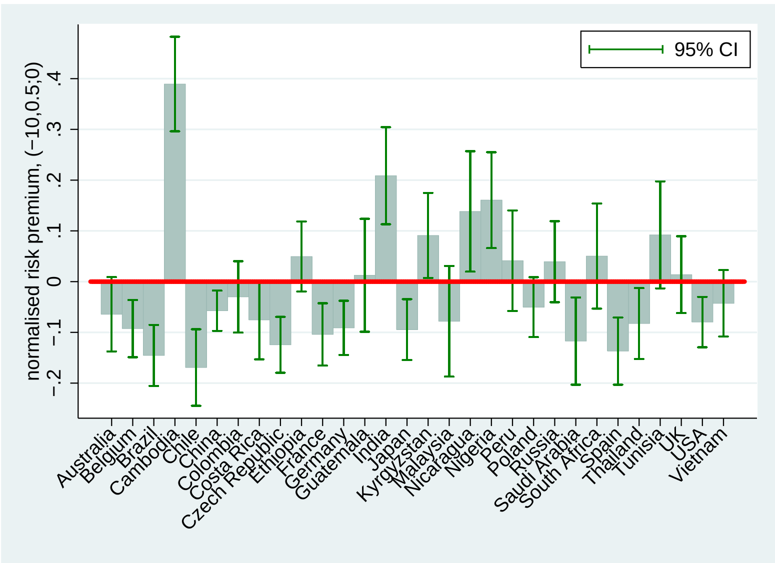


Figure 7: Relative risk premia for (-10,0.5;0)

B Country regression table

dep. var: λ	behavioural	CPT	LU	OPT equal weights	OPT edited	EUT	EUT restricted
Australia	0.026	-0.040	-0.065	-0.098	0.052	-0.105	-0.036
	(0.125)	(0.113)	(0.130)	(0.133)	(0.146)	(0.142)	(0.098)
Belgium	0.004	0.005	0.115	0.122	-0.078	0.126	0.053
	(0.113)	(0.118)	(0.130)	(0.142)	(0.149)	(0.153)	(0.094)
Brazil	-0.048	-0.017	0.133	0.184	-0.176	0.207	0.105
	(0.119)	(0.117)	(0.125)	(0.140)	(0.141)	(0.159)	(0.103)
Cambodia	0.145	1.346***	1.147***	1.587***	1.067***	1.622***	0.265*
	(0.149)	(0.253)	(0.260)	(0.292)	(0.286)	(0.316)	(0.149)
Chile	0.055	0.028	0.028	0.006	0.088	0.012	0.057
	(0.108)	(0.104)	(0.114)	(0.125)	(0.140)	(0.135)	(0.085)
China	0.038	0.211**	0.090	0.163	0.318**	0.155	0.080
	(0.102)	(0.093)	(0.104)	(0.108)	(0.129)	(0.115)	(0.078)
Colombia	0.317***	0.446***	0.542***	0.552***	0.279	0.582***	0.322***
	(0.110)	(0.141)	(0.142)	(0.159)	(0.170)	(0.168)	(0.093)
Costarica	0.099	0.262**	0.169	0.190	0.406**	0.230	0.110
	(0.118)	(0.126)	(0.137)	(0.144)	(0.179)	(0.162)	(0.102)
Czech	-0.098	0.010	-0.004	0.063	-0.032	0.062	0.013
	(0.103)	(0.103)	(0.111)	(0.122)	(0.124)	(0.132)	(0.083)
Ethiopia	0.200*	0.919***	0.768***	1.092***	0.708***	1.220***	0.469***
	(0.112)	(0.157)	(0.161)	(0.201)	(0.160)	(0.235)	(0.117)
France	0.067	-0.015	0.191	0.149	-0.168	0.168	0.069
	(0.110)	(0.112)	(0.124)	(0.134)	(0.135)	(0.142)	(0.085)
Germany	-0.113	-0.149*	-0.079	-0.082	-0.199*	-0.091	-0.104
	(0.105)	(0.090)	(0.107)	(0.112)	(0.113)	(0.119)	(0.077)
Guatemala	-0.253**	0.173	-0.060	0.158	0.223	0.133	-0.161*
	(0.112)	(0.156)	(0.136)	(0.183)	(0.203)	(0.188)	(0.089)
India	0.543***	0.837***	0.814***	0.610***	1.182***	0.812***	0.360**
	(0.180)	(0.183)	(0.218)	(0.190)	(0.268)	(0.218)	(0.154)
Japan	0.077	0.151	0.208*	0.231*	0.077	0.270*	0.163*
	(0.115)	(0.110)	(0.125)	(0.131)	(0.133)	(0.143)	(0.090)
Kyrgyzstan	-0.199*	0.237*	0.100	0.328**	0.176	0.345*	-0.051
	(0.108)	(0.126)	(0.136)	(0.166)	(0.161)	(0.180)	(0.092)
Malaysia	0.399**	0.636***	0.577**	0.666***	0.609***	0.710***	0.507***
	(0.158)	(0.203)	(0.226)	(0.249)	(0.206)	(0.273)	(0.172)
Nicaragua	0.429***	1.207***	1.262***	1.513***	0.880***	2.007***	0.935***
	(0.161)	(0.269)	(0.288)	(0.333)	(0.257)	(0.456)	(0.222)
Nigeria	0.321**	1.165***	0.974***	1.385***	0.740***	1.304***	0.511***
	(0.144)	(0.220)	(0.229)	(0.263)	(0.217)	(0.261)	(0.146)
Peru	0.056	0.658***	0.537***	0.840***	0.533**	0.985***	0.335**
	(0.129)	(0.191)	(0.194)	(0.244)	(0.216)	(0.297)	(0.148)
Poland	0.008	0.157	0.144	0.222*	0.072	0.211	0.042
	(0.119)	(0.111)	(0.127)	(0.133)	(0.139)	(0.142)	(0.091)
Russia	0.085	0.406***	0.364**	0.468***	0.345**	0.495**	0.118
	(0.135)	(0.144)	(0.172)	(0.181)	(0.167)	(0.196)	(0.112)
Saudi	-0.011	0.337**	0.309**	0.554***	0.197	0.671***	0.300***
	(0.116)	(0.135)	(0.125)	(0.161)	(0.168)	(0.193)	(0.116)
South Africa	0.028	0.364**	0.154	0.239	0.557***	0.270	0.032
	(0.127)	(0.145)	(0.147)	(0.167)	(0.212)	(0.181)	(0.105)
Spain	-0.016	0.029	0.075	0.119	-0.081	0.117	0.065
	(0.106)	(0.103)	(0.115)	(0.126)	(0.117)	(0.135)	(0.087)
Thailand	0.162	0.321**	0.439***	0.510***	0.065	0.544***	0.280**
	(0.143)	(0.157)	(0.167)	(0.193)	(0.175)	(0.211)	(0.123)
Tunisia	0.194	0.565***	0.359**	0.432**	0.837***	0.474**	0.167
	(0.152)	(0.191)	(0.180)	(0.198)	(0.297)	(0.212)	(0.128)
UK	0.502***	1.128***	1.398***	1.658***	0.371**	1.930***	0.980***
	(0.153)	(0.203)	(0.228)	(0.242)	(0.165)	(0.305)	(0.190)
Vietnam	-0.108	0.096	0.137	0.246*	-0.003	0.282*	0.027
	(0.107)	(0.120)	(0.119)	(0.142)	(0.156)	(0.156)	(0.086)
female	0.100***	-0.053	-0.022	-0.108**	0.048	-0.110**	0.004
	(0.032)	(0.041)	(0.040)	(0.045)	(0.061)	(0.049)	(0.030)
constant	1.761***	1.324***	1.622***	1.393***	1.198***	1.420***	1.623***
	(0.088)	(0.070)	(0.088)	(0.088)	(0.097)	(0.095)	(0.064)

* , ** , *** indicate significance at the 10, 5 and 1 % level respectively

C Principal characteristics country by country

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	Université de Liège	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 Administrão, 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	Université de 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 Marroquìn	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 Còrdobas	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 Perù	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	Pompeu Fabra University	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	Université 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 were available, else from the CIA World Factbook; 2011 or closest available
GDP refers to 2011 values in PPP, current US Dollars; source: World Bank

References

Abdellaoui, Mohammed (2000) 'Parameter-Free Elicitation of Utility and Probability Weighting Functions.' *Management Science* 46(11), 1497–1512

Abdellaoui, Mohammed, Han Bleichrodt, and Corina Paraschiv (2007) 'Loss Aversion Under Prospect Theory: A Parameter-Free Measurement.' *Management Science* 53(10), 1659–1674

Abdellaoui, Mohammed, Han Bleichrodt, and Olivier L'Haridon (2008) 'A tractable method to measure utility and loss aversion under prospect theory.' *Journal of Risk and Uncertainty* 36(3), 245–266

Andersson, Ola, Håkan J. Holm, Jean-Robert Tyran, and Erik Wengström (2015) 'Deciding for Others Reduces Loss Aversion.' *Management Science, forthcoming*

Ashraf, Quamrul, and Oded Galor (2013) 'The "Out of Africa" Hypothesis, Human Genetic Diversity, and Comparative Economic Development.' *The American Economic Review* 103(1), 1–46

Balafoutas, Loukas, and Matthias Sutter (2012) 'Affirmative Action Policies Promote Women and Do Not Harm Efficiency in the Laboratory.' *Science* 335(6068), 579–582

Baltussen, Guido, Thierry Post, and Pim van Vliet (2006) 'Violations of Cumulative Prospect Theory in Mixed Gambles with Moderate Probabilities.' *Management Science* 52(8), 1288–1290

Barberis, Nicholas C. (2013) 'Thirty Years of Prospect Theory in Economics: A Review and Assessment.' *Journal of Economic Perspectives* 27(1), 173–96

Bateman, Ian, Daniel Kahneman, Alistair Munro, Chris Starmer, and Robert Sugden (2005) 'Testing competing models of loss aversion: an adversarial collaboration.' *Journal of Public Economics* 89(8), 1561–1580

Beauchamp, Jonathan P., Daniel J. Benjamin, Christopher F. Chabris, and David I. Laibson (2012) *How malleable are risk preferences and loss aversion* (WP)

Benartzi, Shlomo, and Richard H Thaler (1995) 'Myopic Loss Aversion and the Equity Premium Puzzle.' *The Quarterly Journal of Economics* 110(1), 73 – 92

Bleichrodt, Han, Jose Maria Abellan-Perpiñan, Jose Luis Pinto-Prades, and Ildefonso Mendez-Martinez (2007) 'Resolving Inconsistencies in Utility Measurement Under Risk: Tests of Generalizations of Expected Utility.' *Management Science* 53(3), 469–482

Booij, Adam S., Bernard M. S. van Praag, and Gijs van de Kuilen (2010) 'A parametric analysis of prospect theory's functionals for the general population.' *Theory and Decision* 68(1-2), 115–148

Booth, Alison L., and Patrick Nolen (2012) 'Gender differences in risk behaviour: does nurture matter?*.' *The Economic Journal* 122(558), F56–F78

Brislin, Richard W. (1970) 'Back-translation for Cross-Cultural Research.' *Journal of Cross-Cultural Psychology* 1(3), 185–216

Brooks, Peter, and Horst Zank (2005) 'Loss Averse Behavior.' *Journal of Risk and Uncertainty* 31(3), 301–325

Brooks, Peter, Simon Peters, and Horst Zank (2014) 'Risk behavior for gain, loss, and mixed prospects.' *Theory and Decision* 77(2), 153–182

Bruhin, Adrian, Helga Fehr-Duda, and Thomas Epper (2010) 'Risk and Rationality: Uncovering Heterogeneity in Probability Distortion.' *Econometrica* 78(4), 1375–1412

Camerer, Colin F. (2000) 'Prospect Theory in the Wild: Evidence from the Field.' In 'Choices, Values, and Frames' (Cambridge: Cambridge University Press)

Croson, Rachel, and Uri Gneezy (2009) 'Gender Differences in Preferences.' *Journal of Economic Literature* 47(2), 1–27

Diecidue, Enrico, and Jeroen van de Ven (2008) 'Aspiration Level, Probability of Success and Failure, and Expected Utility.' *International Economic Review* 49(2), 683–700

Dohmen, Thomas, Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, and Gert G. Wagner (2011) 'Individual Risk Attitudes: Measurement, Determinants, and Behavioral Consequences.' *Journal of the European Economic Association* 9(3), 522–550

Filippin, Antonio, and Paolo Crosetto (2014) 'A Reconsideration of Gender Differences in Risk Attitudes.' SSRN Scholarly Paper ID 2441480, Social Science Research Network, Rochester, NY, May

Gächter, Simon, Eric J. Johnson, and Andreas Herrmann (2010) 'Individual-level loss aversion in riskless and risky choices.' Technical Report 2010-20, CeDEx discussion paper series

Gallup, John Luke, Jeffrey D. Sachs, and Andrew D. Mellinger (1999) 'Geography and Economic Development.' *International Regional Science Review* 22(2), 179–232

Gneezy, Uri, and Jan Potters (1997) 'An Experiment on Risk Taking and Evaluation Periods.' *The Quarterly Journal of Economics* 112(2), 631 – 45

Goette, Lorenz, David Huffman, and Ernst Fehr (2004) 'Loss Aversion and Labor Supply.' *Journal of the European Economic Association* 2(2-3), 216–228

Haigh, Michael S., and John A. List (2005) 'Do Professional Traders Exhibit Myopic Loss Aversion? An Experimental Analysis.' *Journal of Finance* 60(1), 523 – 534

Harrison, Glenn W., and E. Elisabet Rutström (2009) 'Expected utility theory and prospect theory: one wedding and a decent funeral.' *Experimental Economics* 12(2), 133–158

Hey, John D., and Chris Orme (1994) 'Investigating Generalizations of Expected Utility Theory Using Experimental Data.' *Econometrica* 62(6), 1291–1326

Holden, Stein T. (2014) 'Risky Choices of Poor People: Comparing Risk Preference Elicitation Approaches in Field Experiments.' *CLTS Working Paper*

Kahneman, Daniel, and Amos Tversky (1979) 'Prospect Theory: An Analysis of Decision under Risk.' *Econometrica* 47(2), 263 – 291

Kahneman, Daniel, Jack L. Knetsch, and Richard H. Thaler (1991) 'Anomalies: The endowment effect, loss aversion, and status quo bias.' *Journal of Economic Perspectives* 5(1), 193–206

Köbberling, Veronika, and Peter P. Wakker (2005) 'An index of loss aversion.' *Journal of Economic Theory* 122(1), 119 – 131

Kocher, Martin G., Julius Pahlke, and Stefan T. Trautmann (2013) 'Tempus Fugit: Time Pressure in Risky Decisions.' *Management Science* 59(10), 2380–2391

Kőszegi, Botond, and Matthew Rabin (2007) 'Reference-Dependent Risk Attitudes.' *The American Economic Review* 97(4), 1047–1073

L'Haridon, Olivier, and Ferdinand M. Vieider (2015) 'All over the map: Heterogeneity of risk preferences across individuals, contexts, and countries.' *Working paper*

Liu, Elaine M. (2012) 'Time to Change What to Sow: Risk Preferences and Technology Adoption Decisions of Cotton Farmers in China.' *Review of Economics and Statistics* 95(4), 1386–1403

Markowitz, Harry (1952) 'The Utility of Wealth.' *Journal of Political Economy* 60(2), 151–158

Nguyen, Quang (2011) 'Does nurture matter: Theory and experimental investigation on the effect of working environment on risk and time preferences.' *Journal of Risk and Uncertainty* 43(3), 245–270

Niederle, Muriel, and Lise Vesterlund (2005) 'Do Women Shy Away From Competition? Do Men Compete Too Much?' Working Paper 11474, National Bureau of Economic Research, July

Pollmann, Monique M. H., Jan Potters, and Stefan T. Trautmann (2014) 'Risk taking by agents: The role of ex-ante and ex-post accountability.' *Economics Letters* 123(3), 387–390

Rabin, Matthew (2000) 'Risk Aversion and Expecetd Utility Theory: A Calibration Theorem.' *Econometrica* 68, 1281–1292

Rieger, Marc Oliver, Mei Wang, and Thorsten Hens (2014) 'Risk Preferences Around the World.' *Management Science* 61(3), 637 – 648

Schmidt, Ulrich, and Horst Zank (2005) 'What is Loss Aversion?' *Journal of Risk and Uncertainty* 30(2), 157–167

_ (2007) 'Linear cumulative prospect theory with applications to portfolio selection and insurance demand.' *Decisions in Economics and Finance* 30(1), 1–18

_ (2008) 'Risk Aversion in Cumulative Prospect Theory.' *Management Science* 54(1), 208–216

Schmidt, Ulrich, and Stefan Traub (2002) 'An Experimental Test of Loss Aversion.' *Journal of Risk and Uncertainty* 25(3), 233–249

Starmer, Chris (2000) 'Developments in Non-Expected Utility Theory: The Hunt for a Descriptive Theory of Choice under Risk.' *Journal of Economic Literature* 38, 332–382

Sugden, Robert (2003) 'Reference-dependent subjective expected utility.' *Journal of Economic Theory* 111(2), 172–191

Sutter, Matthias (2007) 'Are teams prone to myopic loss aversion? An experimental study on individual versus team investment behavior.' *Economics Letters* 97(2), 128 – 132

Tanaka, Tomomi, Colin F. Camerer, and Quang Nguyen (2010) 'Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam.' *American Economic Review* 100(1), 557–571

Train, Kenneth (2009) *Discrete choice methods with simulation* (Cambridge; New York: Cambridge University Press)

Tversky, Amos (1972) 'Elimination by aspects: A theory of choice.' *Psychological Review* 79(4), 281–299

Tversky, Amos, and Daniel Kahneman (1992) 'Advances in Prospect Theory: Cumulative Representation of Uncertainty.' *Journal of Risk and Uncertainty* 5, 297–323

Vieider, Ferdinand M. (2012) 'Moderate stake variations for risk and uncertainty, gains and losses: methodological implications for comparative studies.' *Economics Letters* 117, 718–721

Vieider, Ferdinand M., Abebe Beyene, Randall A. Bluffstone, Sahan Dissanayake, Zenebe Gebreegziabher, Peter Martinsson, and Alemu Mekonnen (2014) 'Measuring risk preferences in Ethiopia: Further evidence on a risk-income paradox, and on risk and religion.' *WZB Working Paper*

Vieider, Ferdinand M., Mathieu Lefebvre, Ranoua Bouchouicha, Thorsten Chmura, Rustamdjan Hakimov, Michal Krawczyk, and Peter Martinsson (2015a) 'Common components of risk and uncertainty attitudes across contexts and domains: Evidence from 30 countries.' *Journal of the European Economic Association* 13(3), 421–452

Vieider, Ferdinand M., Nghi Truong, Peter Martinsson, and Nam Pham Khanh (2013) 'Risk Preferences and Development Revisited.' *WZB Discussion Paper SP II 2013–403*

Vieider, Ferdinand M., Thorsten Chmura, and Peter Martinsson (2012) 'Risk Attitudes, Development, and Growth. Macroeconomic Evidence from Experiments in 30 Countries.' *WZB Working paper*

Vieider, Ferdinand M., Thorsten Chmura, Tylor Fisher, Takao Kusakawa, Peter Martinsson, Frauke Mattison Thompson, and Adewara Sunday (2015b) 'Within- versus Between-Country Differences in Risk Attitudes: Implications for Cultural Comparisons.' *Theory and Decision* 78(2), 209–218

Villeval, Marie Claire (2012) 'Ready, Steady, Compete.' *Science* 335(6068), 544–545

von Gaudecker, Hans-Martin, Arthur van Soest, and Erik Wengström (2011) 'Heterogeneity in Risky Choice Behaviour in a Broad Population.' *American Economic Review* 101(2), 664–694

Wakker, Peter P. (2010) *Prospect Theory for Risk and Ambiguity* (Cambridge: Cambridge University Press)

Wu, George, and Alex B. Markle (2008) 'An Empirical Test of Gain-Loss Separability in Prospect Theory.' *Management Science* 54(7), 1322–1335

Yaari, Menahem E. (1987) 'The Dual Theory of Choice under Risk.' *Econometrica* 55(1), 95–115

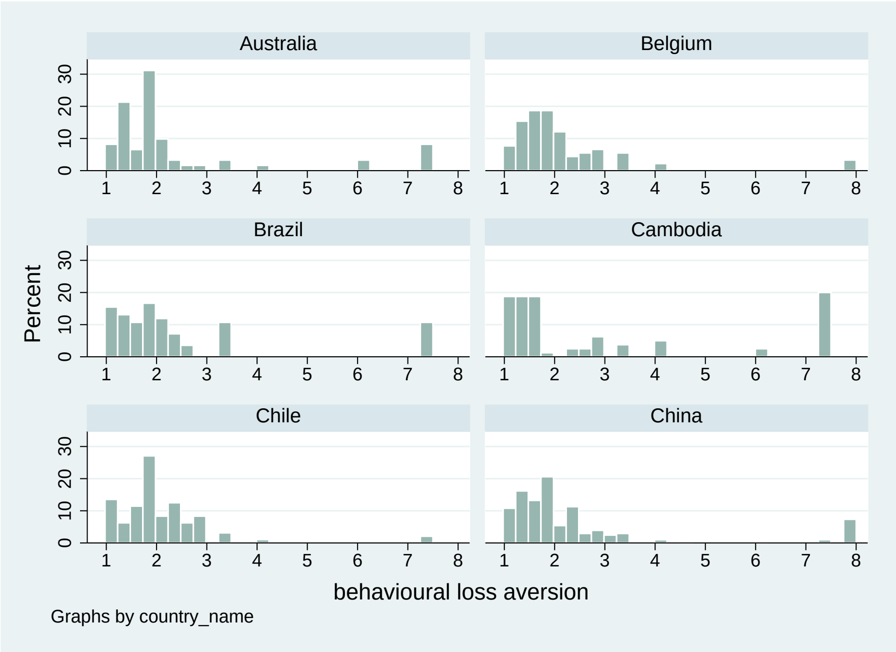
Zank, Horst (2010) 'On probabilities and loss aversion.' *Theory and Decision* 68(3), 243–261

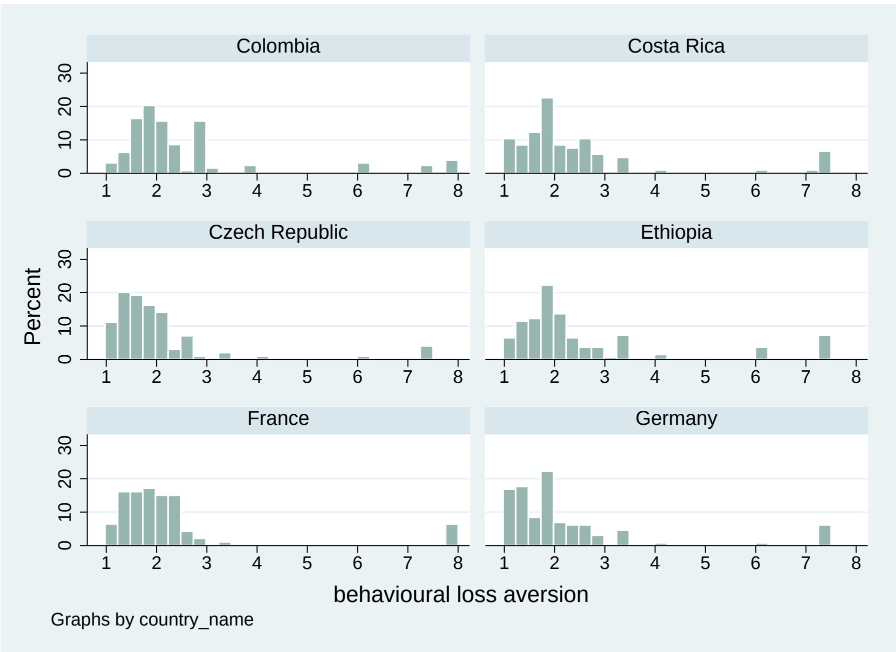
Zeisberger, Stefan, Dennis Vrecko, and Thomas Langer (2012) 'Measuring the time stability of Prospect Theory preferences.' *Theory and Decision* 72(3), 359–386

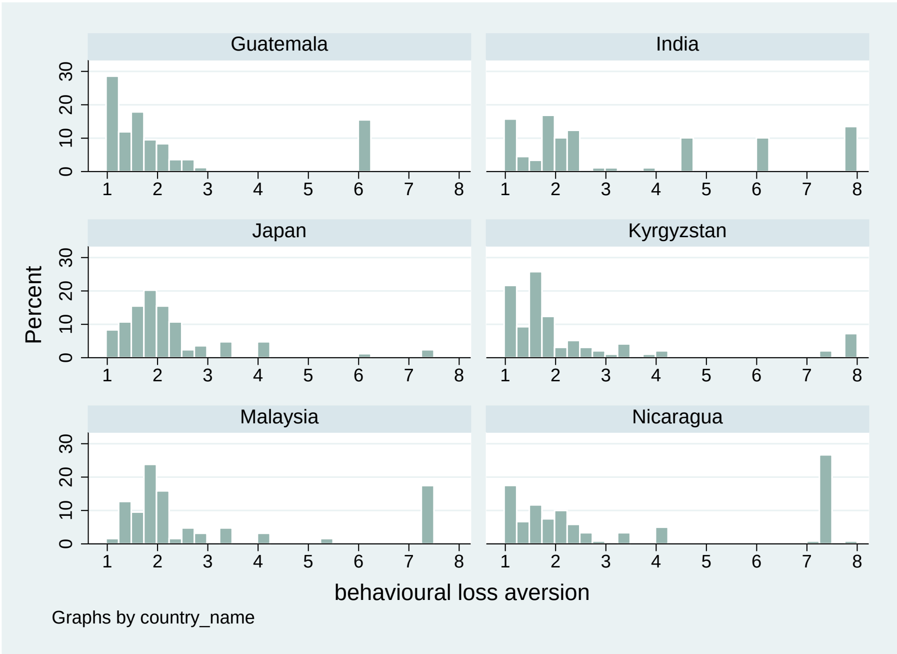
SUPPLEMENTRAY MATERIALS FOR ONLINE PUBLICATION

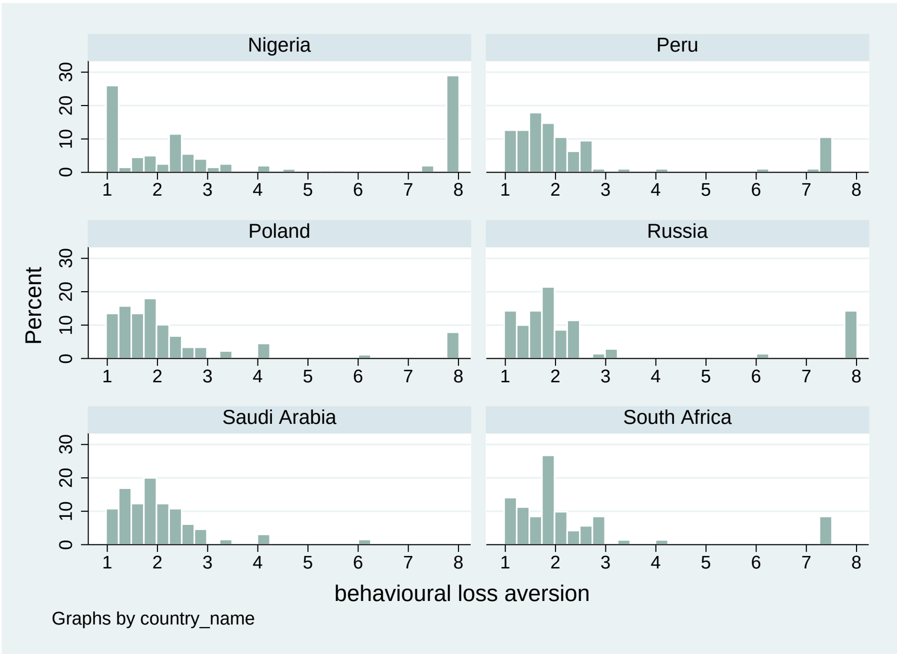
Behavioural loss aversion country by country

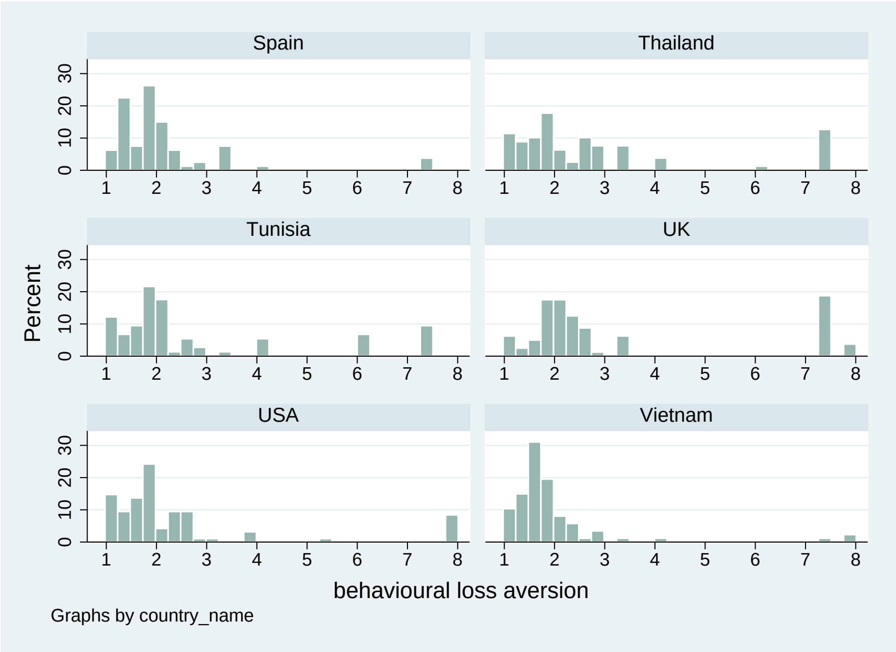
Countries in alphabetical order.






Guatemala
India
Japan
Kyrgyzstan
Malaysia
Nicaragua
Percent
0 10 20 30
1 2 3 4 5 6 7 8
behavioural loss aversion
Graphs by country_name


Nigeria
Peru
Poland
Russia
Saudi Arabia
South Africa
Percent
0 10 20 30
1 2 3 4 5 6 7 8
behavioural loss aversion
Graphs by country_name


Spain
Thailand
Tunisia
UK
USA
Vietnam
Percent
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3
4
5
6
7
8
behavioural loss aversion
Graphs by country_name

Complete between-country regressions

In this section, we report the full regressions underlying the between-country regression results for the loss aversion parameters in the main text.

Table A.1: CPT defintion, between-country regression

	μ	ν	λ	π^+	π^-	σ
GDP p.c. (diff. from US)	-0.006**	0.014***	0.200***	-0.002	-0.008	0.033***
	(0.003)	(0.005)	(0.048)	(0.007)	(0.009)	(0.003)
predicted genetic div.	0.004	0.028**	-0.067	0.008	0.057***	-0.046***
	(0.006)	(0.011)	(0.116)	(0.017)	(0.020)	(0.007)
genetic diversity squared	0.003	-0.005	-0.117**	0.011	0.011	-0.022***
	(0.003)	(0.005)	(0.050)	(0.008)	(0.009)	(0.003)
minutes latitude	-0.000	0.000	-0.005**	-0.001*	0.001	-0.000**
	(0.000)	(0.000)	(0.003)	(0.000)	(0.001)	(0.000)
foreigner	0.002	-0.003	-0.047	0.004	-0.006	0.015**
	(0.006)	(0.010)	(0.083)	(0.017)	(0.016)	(0.007)
Gini	-0.004**	0.001	0.017	-0.013**	-0.002	-0.004*
	(0.002)	(0.004)	(0.038)	(0.006)	(0.007)	(0.002)
private university	-0.003	0.005	0.051	0.013	0.010	0.013**
	(0.005)	(0.009)	(0.091)	(0.015)	(0.017)	(0.006)
OPEC	-0.012**	-0.035***	0.242	0.014	-0.073***	0.067***
	(0.006)	(0.013)	(0.149)	(0.021)	(0.023)	(0.007)
Africa	-0.001	0.023*	0.047	-0.039*	0.054**	0.010
	(0.007)	(0.012)	(0.124)	(0.020)	(0.024)	(0.009)
Asia	0.008	0.028**	-0.260**	0.004	0.100***	-0.067***
	(0.006)	(0.012)	(0.111)	(0.018)	(0.021)	(0.008)
Americas	0.009	0.086***	-0.114	0.001	0.168***	-0.047***
	(0.011)	(0.021)	(0.190)	(0.035)	(0.038)	(0.015)
Oceania	0.003	0.065***	-0.255	-0.047	0.139***	-0.063***
	(0.012)	(0.020)	(0.191)	(0.035)	(0.038)	(0.014)
female	0.006**	0.003	-0.034	-0.017**	0.006	0.014***
	(0.002)	(0.004)	(0.041)	(0.007)	(0.008)	(0.003)
gain						-0.001
						(0.002)
constant	0.037***	-0.044***	1.731***	0.582***	0.401***	0.223***
	(0.008)	(0.015)	(0.149)	(0.023)	(0.028)	(0.009)

* , ** , *** indicate significance at the 10, 5 and 1 % level respectively

Table A.2: LU definition, between-country regression

	λ	π^+	π^-	σ
GDP p.d. (diff. from US)	0.124***	0.009	-0.029***	0.032***
	(0.047)	(0.005)	(0.006)	(0.003)
predicted genetic div.	-0.161	0.000	0.017	-0.045***
	(0.114)	(0.013)	(0.013)	(0.007)
genetic diversity squared	-0.085*	0.006	0.019***	-0.022***
	(0.048)	(0.006)	(0.006)	(0.003)
minutes latitude	-0.009***	-0.001*	0.000	-0.000**
	(0.003)	(0.000)	(0.000)	(0.000)
foreigner	-0.024	0.001	-0.002	0.015**
	(0.083)	(0.013)	(0.012)	(0.007)
Gini	-0.019	-0.005	-0.003	-0.005*
	(0.036)	(0.004)	(0.004)	(0.002)
private university	0.030	0.018	0.001	0.013**
	(0.089)	(0.011)	(0.012)	(0.006)
OPEC	0.287*	0.038**	-0.022	0.066***
	(0.158)	(0.015)	(0.017)	(0.007)
Africa	-0.102	-0.036**	0.020	0.011
	(0.122)	(0.015)	(0.016)	(0.009)
Asia	-0.379***	-0.011	0.059***	-0.066***
	(0.114)	(0.014)	(0.014)	(0.008)
Americas	-0.452**	-0.018	0.043*	-0.045***
	(0.203)	(0.026)	(0.026)	(0.015)
Oceania	-0.592***	-0.053**	0.045*	-0.063***
	(0.193)	(0.026)	(0.024)	(0.014)
female	-0.005	-0.028***	0.002	0.014***
	(0.043)	(0.005)	(0.005)	(0.003)
gain				0.002
				(0.002)
constant	2.356***	0.510***	0.465***	0.222***
	(0.150)	(0.018)	(0.019)	(0.009)

* , ** , *** indicate significance at the 10, 5 and 1 % level respectively

Table A.3: OPT equal weights, between-country regression

	μ	ν	λ	π^+	σ
GDP p.c. (diff. from US)	-0.006**	0.017***	0.219***	-0.003	0.033***
	(0.002)	(0.004)	(0.056)	(0.006)	(0.003)
predicted genetic div.	0.010*	0.010	-0.168	0.025*	-0.046***
	(0.005)	(0.011)	(0.134)	(0.013)	(0.007)
genetic diversity squared	0.002	-0.005	-0.119**	0.011*	-0.022***
	(0.002)	(0.005)	(0.059)	(0.006)	(0.003)
minutes latitude	0.000	-0.000	-0.009***	-0.000	-0.000**
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)
foreigner	0.000	0.000	-0.024	-0.000	0.015**
	(0.005)	(0.009)	(0.096)	(0.012)	(0.007)
Gini	-0.002	-0.004	-0.012	-0.009**	-0.004*
	(0.002)	(0.003)	(0.043)	(0.004)	(0.002)
private university	-0.003	0.006	0.062	0.012	0.013**
	(0.004)	(0.008)	(0.104)	(0.011)	(0.006)
OPEC	-0.024***	-0.002	0.481***	-0.016	0.067***
	(0.006)	(0.014)	(0.179)	(0.016)	(0.007)
Africa	0.014**	-0.009	-0.154	-0.003	0.010
	(0.006)	(0.011)	(0.140)	(0.015)	(0.009)
Asia	0.021***	-0.007	-0.465***	0.038***	-0.068***
	(0.006)	(0.011)	(0.132)	(0.014)	(0.008)
Americas	0.033***	0.025	-0.445**	0.060**	-0.048***
	(0.010)	(0.021)	(0.223)	(0.026)	(0.015)
Oceania	0.030***	-0.003	-0.639***	0.020	-0.065***
	(0.011)	(0.019)	(0.219)	(0.027)	(0.014)
female	0.008***	-0.006	-0.094*	-0.010*	0.014***
	(0.002)	(0.004)	(0.048)	(0.005)	(0.003)
gain					-0.001
					(0.002)
constant	0.010	0.022	2.120***	0.516***	0.224***
	(0.007)	(0.014)	(0.177)	(0.017)	(0.009)

* , ** , *** indicate significance at the 10, 5 and 1 % level respectively

Table A.4: OPT edited, between-country regression

	μ	ν	λ	π^+	π^-	σ
GDP p.c. (diff. from US)	-0.008***	0.017***	0.208***	-0.006	-0.004	0.033***
	(0.003)	(0.005)	(0.065)	(0.008)	(0.009)	(0.003)
predicted genetic dist.	0.006	0.025**	0.042	0.013	0.053***	-0.046***
	(0.006)	(0.011)	(0.145)	(0.018)	(0.020)	(0.007)
genetic distance sqaured	0.004	-0.007	-0.134**	0.014*	0.008	-0.021***
	(0.003)	(0.005)	(0.059)	(0.008)	(0.009)	(0.003)
minutes latitude	-0.000	0.000	0.001	-0.001**	0.001*	-0.000**
	(0.000)	(0.000)	(0.004)	(0.000)	(0.001)	(0.000)
foreigner	0.004	-0.006	-0.103	0.008	-0.012	0.015**
	(0.006)	(0.010)	(0.097)	(0.017)	(0.016)	(0.007)
Gini	-0.007***	0.005	0.123**	-0.018***	0.005	-0.004*
	(0.002)	(0.004)	(0.052)	(0.006)	(0.007)	(0.002)
private university	-0.003	0.005	0.048	0.013	0.009	0.013**
	(0.005)	(0.009)	(0.117)	(0.015)	(0.017)	(0.006)
OPEC	-0.012*	-0.038***	-0.132	0.015	-0.080***	0.067***
	(0.006)	(0.013)	(0.169)	(0.020)	(0.024)	(0.007)
Africa	-0.002	0.023*	0.302*	-0.040*	0.053**	0.010
	(0.007)	(0.013)	(0.157)	(0.020)	(0.024)	(0.009)
Asia	0.012*	0.023**	-0.062	0.012	0.092***	-0.067***
	(0.006)	(0.011)	(0.128)	(0.018)	(0.021)	(0.008)
Americas	0.015	0.079***	0.238	0.012	0.159***	-0.047***
	(0.012)	(0.021)	(0.254)	(0.035)	(0.039)	(0.015)
Oceania	0.004	0.065***	0.269	-0.045	0.141***	-0.064***
	(0.012)	(0.020)	(0.242)	(0.036)	(0.038)	(0.014)
female	0.006**	0.004	0.041	-0.018**	0.009	0.014***
	(0.002)	(0.004)	(0.052)	(0.007)	(0.008)	(0.003)
gain						-0.001
						(0.002)
constant	0.039***	-0.046***	1.189***	0.585***	0.397***	0.223***
	(0.008)	(0.016)	(0.202)	(0.024)	(0.029)	(0.009)

* , ** , *** indicate significance at the 10, 5 and 1 % level respectively

Table A.5: EUT, between-country regression

	μ	ν	λ	σ
GDP p.c. (diff. from US)	-0.005**	0.019***	0.228***	0.033***
	(0.002)	(0.003)	(0.061)	(0.003)
predicted genetic diversity	0.001	-0.006	-0.152	-0.046***
	(0.005)	(0.008)	(0.149)	(0.007)
genetic diversity squared	-0.002	-0.012***	-0.113*	-0.021***
	(0.002)	(0.004)	(0.065)	(0.003)
minutes latitude	0.000	-0.000	-0.010***	-0.000**
	(0.000)	(0.000)	(0.003)	(0.000)
foreigner	0.000	0.001	-0.024	0.015**
	(0.005)	(0.007)	(0.104)	(0.007)
Gini	0.001	0.002	-0.026	-0.004*
	(0.002)	(0.003)	(0.046)	(0.002)
private university	-0.008*	-0.000	0.091	0.014**
	(0.004)	(0.007)	(0.117)	(0.006)
OPEC	-0.018***	0.009	0.499**	0.068***
	(0.006)	(0.011)	(0.202)	(0.007)
Africa	0.014**	-0.008	-0.183	0.010
	(0.006)	(0.010)	(0.152)	(0.009)
Asia	0.006	-0.029***	-0.459***	-0.067***
	(0.005)	(0.009)	(0.146)	(0.008)
Americas	0.009	-0.012	-0.420*	-0.047***
	(0.010)	(0.016)	(0.247)	(0.015)
Oceania	0.022**	-0.016	-0.656***	-0.064***
	(0.011)	(0.014)	(0.240)	(0.014)
female	0.012***	-0.001	-0.102*	0.013***
	(0.002)	(0.003)	(0.053)	(0.003)
gain				0.001
				(0.002)
constant	0.004	0.013	2.188***	0.223***
	(0.007)	(0.011)	(0.194)	(0.009)

* , ** , *** indicate significance at the 10, 5 and 1 % level respectively

Table A.6: EUT restricted, between-country regression

	μ	λ	σ
GDP p.c. (diff. from US)	-0.005**	0.008	0.029***
	(0.002)	(0.033)	(0.003)
predicted genetic diversity	0.001	-0.054	-0.032***
	(0.005)	(0.083)	(0.007)
genetic diversity squared	-0.002	-0.005	-0.018***
	(0.003)	(0.035)	(0.003)
minutes latitude	0.000*	-0.008***	-0.000*
	(0.000)	(0.002)	(0.000)
foreigner	-0.001	-0.021	0.016**
	(0.005)	(0.066)	(0.007)
Gini	0.002	-0.020	-0.004
	(0.002)	(0.026)	(0.003)
private university	-0.008*	0.043	0.012**
	(0.004)	(0.069)	(0.006)
OPEC	-0.018***	0.157	0.055***
	(0.006)	(0.108)	(0.007)
Africa	0.014**	-0.041	0.003
	(0.006)	(0.089)	(0.010)
Asia	0.006	-0.125	-0.057***
	(0.006)	(0.082)	(0.009)
Americas	0.009	-0.215	-0.022
	(0.010)	(0.151)	(0.016)
Oceania	0.023**	-0.318**	-0.032**
	(0.011)	(0.144)	(0.016)
female	0.012***	0.002	0.007**
	(0.002)	(0.031)	(0.003)
constant	0.003	2.105***	0.220***
	(0.007)	(0.108)	(0.010)

* , ** , *** indicate significance at the 10, 5 and 1 % level respectively

Complete individual level regressions

Table A.7: CPT, individual regressions

	μ	ν	λ	π^+	π^-	σ
female	0.004*	-0.004	-0.065	-0.015**	0.003	0.007**
	(0.003)	(0.005)	(0.042)	(0.007)	(0.008)	(0.003)
age	-0.002	0.008***	0.062***	-0.004	0.006	0.007***
	(0.001)	(0.003)	(0.023)	(0.005)	(0.004)	(0.002)
height	0.001	0.004	-0.003	0.005	0.002	-0.001
	(0.002)	(0.003)	(0.025)	(0.004)	(0.005)	(0.002)
GPA	0.003*	-0.004	-0.077***	0.005	0.004	-0.006***
	(0.001)	(0.003)	(0.023)	(0.004)	(0.005)	(0.002)
math	-0.003	0.002	-0.069	-0.007	0.007	-0.002
	(0.004)	(0.007)	(0.068)	(0.011)	(0.012)	(0.005)
natural	0.002	-0.005	-0.134	-0.002	0.002	0.006
	(0.006)	(0.009)	(0.085)	(0.016)	(0.018)	(0.006)
medicine	0.005	0.028**	-0.070	0.004	0.068***	-0.002
	(0.007)	(0.012)	(0.098)	(0.020)	(0.020)	(0.009)
social	-0.001	-0.004	-0.039	-0.020	-0.006	0.014***
	(0.005)	(0.008)	(0.071)	(0.014)	(0.016)	(0.005)
humanities	0.004	0.020*	0.038	-0.005	0.027	0.016**
	(0.006)	(0.011)	(0.098)	(0.016)	(0.017)	(0.007)
arts	0.001	0.021	0.198	0.023	0.024	0.015*
	(0.009)	(0.018)	(0.154)	(0.028)	(0.031)	(0.008)
study other	-0.006	0.006	-0.000	-0.029**	0.013	0.016***
	(0.005)	(0.007)	(0.068)	(0.013)	(0.014)	(0.005)
country dummies	✓	✓	✓	✓	✓	✓
gain						0.000
						(0.002)
constant	0.038***	0.004	1.433***	0.546***	0.503***	0.172***
	(0.006)	(0.009)	(0.086)	(0.018)	(0.019)	(0.009)
N_clust	2939					
chi2	103.35					

* , ** , *** indicate significance at the 10, 5 and 1 % level respectively

Table A.8: LU, individual regression

	λ	π^+	π^-	σ
female	-0.026	-0.024***	0.008	0.008***
	(0.040)	(0.005)	(0.005)	(0.003)
age	0.023	-0.001	-0.006*	0.007***
	(0.023)	(0.003)	(0.003)	(0.002)
height_norm_sex	-0.009	0.003	-0.004	-0.001
	(0.025)	(0.003)	(0.003)	(0.002)
GPA	-0.054**	-0.000	0.009***	-0.005***
	(0.024)	(0.003)	(0.003)	(0.002)
math	-0.126*	-0.001	0.004	-0.002
	(0.065)	(0.008)	(0.008)	(0.005)
natural	-0.118	-0.007	0.008	0.006
	(0.085)	(0.011)	(0.010)	(0.006)
medicine	-0.167*	-0.005	0.027*	-0.002
	(0.090)	(0.016)	(0.016)	(0.009)
social	-0.049	-0.019*	-0.001	0.014***
	(0.074)	(0.010)	(0.011)	(0.005)
humanities	-0.009	-0.013	-0.002	0.017**
	(0.093)	(0.012)	(0.012)	(0.007)
arts	0.159	0.021	-0.007	0.015*
	(0.168)	(0.020)	(0.019)	(0.009)
study other	-0.082	-0.017*	0.004	0.016***
	(0.065)	(0.009)	(0.009)	(0.005)
country dummies	✓	✓	✓	✓
gain				0.003
				(0.002)
constant	1.740***	0.472***	0.496***	0.172***
	(0.098)	(0.013)	(0.012)	(0.009)
N clusters	2939			
chi2	201.53			

* , ** , *** indicate significance at the 10, 5 and 1 % level respectively

Table A.9: OPT equal weights, individual regression

	μ	ν	λ	π^+	σ
female	0.006***	-0.011***	-0.115**	-0.010*	0.007**
	(0.002)	(0.004)	(0.045)	(0.006)	(0.003)
age	-0.000	0.004*	0.041*	-0.000	0.007***
	(0.001)	(0.002)	(0.025)	(0.003)	(0.002)
height	0.001	0.006**	0.007	0.004	-0.001
	(0.001)	(0.002)	(0.027)	(0.003)	(0.002)
GPA	0.003**	-0.003	-0.077***	0.005	-0.006***
	(0.001)	(0.003)	(0.026)	(0.003)	(0.002)
math	-0.001	-0.003	-0.096	-0.002	-0.002
	(0.003)	(0.006)	(0.074)	(0.008)	(0.005)
natural	0.003	-0.006	-0.148	-0.001	0.006
	(0.005)	(0.008)	(0.093)	(0.012)	(0.006)
medicine	0.015**	0.005	-0.195*	0.027*	-0.004
	(0.006)	(0.012)	(0.109)	(0.015)	(0.009)
social	0.001	-0.009	-0.076	-0.016	0.013***
	(0.004)	(0.008)	(0.083)	(0.010)	(0.005)
humanities	0.009*	0.008	-0.029	0.007	0.016**
	(0.005)	(0.010)	(0.104)	(0.012)	(0.007)
arts	0.003	0.023	0.194	0.026	0.015*
	(0.007)	(0.018)	(0.176)	(0.021)	(0.008)
study other	-0.001	-0.010	-0.080	-0.015	0.016***
	(0.004)	(0.007)	(0.075)	(0.009)	(0.005)
country dummies	✓	✓	✓	✓	✓
gain					-0.000
					(0.002)
constant	0.032***	0.021**	1.531***	0.531***	0.172***
	(0.006)	(0.010)	(0.101)	(0.012)	(0.009)
N_clust	2939				
chi2	161.61				

* , ** , *** indicate significance at the 10, 5 and 1 % level respectively

Table A.10: OPT edited, individual regression

	μ	ν	λ	π^+	π^-	σ
female	0.002	0.001	0.048	-0.020**	0.010	0.007**
	(0.003)	(0.005)	(0.066)	(0.008)	(0.009)	(0.003)
age	-0.002	0.009***	0.096***	-0.005	0.007	0.007***
	(0.002)	(0.003)	(0.035)	(0.005)	(0.004)	(0.002)
height	0.001	0.004	-0.018	0.006	0.002	-0.001
	(0.002)	(0.003)	(0.044)	(0.005)	(0.005)	(0.002)
GPA	0.003	-0.003	-0.065**	0.004	0.004	-0.006***
	(0.002)	(0.003)	(0.032)	(0.004)	(0.005)	(0.002)
math	-0.001	-0.002	-0.080	-0.003	0.001	-0.001
	(0.005)	(0.008)	(0.118)	(0.013)	(0.014)	(0.005)
natural	0.005	-0.011	-0.189	0.004	-0.008	0.006
	(0.007)	(0.010)	(0.143)	(0.018)	(0.019)	(0.006)
medicine	0.007	0.025**	0.054	0.007	0.063***	-0.002
	(0.007)	(0.012)	(0.137)	(0.020)	(0.021)	(0.009)
social	-0.004	0.004	0.091	-0.028*	0.006	0.014***
	(0.005)	(0.009)	(0.115)	(0.015)	(0.017)	(0.005)
humanities	0.005	0.018	0.104	-0.004	0.023	0.016**
	(0.006)	(0.012)	(0.133)	(0.016)	(0.018)	(0.007)
arts	0.003	0.012	0.084	0.029	0.008	0.015*
	(0.009)	(0.017)	(0.224)	(0.028)	(0.030)	(0.008)
study other	-0.002	0.000	0.012	-0.021	0.005	0.016***
	(0.005)	(0.008)	(0.100)	(0.013)	(0.015)	(0.005)
country dummies	✓	✓	✓	✓	✓	✓
gain						0.000
						(0.002)
constant	0.040***	0.002	1.276***	0.550***	0.498***	0.172***
	(0.008)	(0.011)	(0.145)	(0.020)	(0.020)	(0.009)
N_clust	2939					
chi2	101.35					

* , ** , *** indicate significance at the 10, 5 and 1 % level respectively

Table A.11: EUT, individual regression

	μ	ν	λ	σ
female	0.010***	-0.005	-0.117**	0.007**
	(0.002)	(0.003)	(0.049)	(0.003)
age	0.000	0.004**	0.040	0.007***
	(0.001)	(0.002)	(0.026)	(0.002)
height	-0.001	0.003*	0.009	-0.001
	(0.001)	(0.002)	(0.029)	(0.002)
GPA	0.001	-0.006***	-0.085***	-0.005***
	(0.001)	(0.002)	(0.029)	(0.002)
math	-0.000	-0.002	-0.115	-0.002
	(0.003)	(0.005)	(0.081)	(0.005)
natural	0.003	-0.006	-0.151	0.006
	(0.004)	(0.006)	(0.099)	(0.006)
medicine	0.003	-0.011	-0.189	-0.003
	(0.007)	(0.010)	(0.120)	(0.009)
social	0.007*	0.000	-0.093	0.013***
	(0.004)	(0.006)	(0.089)	(0.005)
humanities	0.006	0.004	-0.024	0.016**
	(0.005)	(0.007)	(0.114)	(0.007)
arts	-0.008	0.006	0.270	0.016**
	(0.008)	(0.012)	(0.223)	(0.008)
study other	0.005	-0.001	-0.084	0.015***
	(0.004)	(0.005)	(0.081)	(0.005)
country dummies	✓	✓	✓	✓
gain				0.002
				(0.002)
constant	0.019***	0.003	1.574***	0.171***
	(0.005)	(0.007)	(0.111)	(0.009)
Nr. clusters	2939			
chi2	214.08			

* , ** , *** indicate significance at the 10, 5 and 1 % level respectively

Table A.12: EUT restricted, individual regression

	μ	λ	σ
female	0.011***	0.000	0.001
	(0.002)	(0.030)	(0.003)
age	0.000	0.003	0.006***
	(0.001)	(0.017)	(0.002)
height	-0.001	-0.028	-0.002
	(0.001)	(0.019)	(0.002)
GPA	0.001	-0.025	-0.003*
	(0.001)	(0.018)	(0.002)
math	-0.000	-0.094*	-0.003
	(0.003)	(0.052)	(0.005)
natural	0.003	-0.073	0.005
	(0.004)	(0.064)	(0.007)
medicine	0.003	-0.085	-0.010
	(0.007)	(0.072)	(0.010)
social	0.009**	-0.061	0.006
	(0.004)	(0.055)	(0.006)
humanities	0.006	-0.006	0.014*
	(0.005)	(0.066)	(0.007)
arts	-0.009	0.128	0.010
	(0.008)	(0.136)	(0.009)
study other	0.006	-0.036	0.012**
	(0.004)	(0.050)	(0.005)
country dummies	✓	✓	✓
constant	0.019***	1.704***	0.193***
	(0.005)	(0.075)	(0.009)
Nr. clusters	2939		
chi2	209.25		

* , ** , *** indicate significance at the 10, 5 and 1 % level respectively

Full-length instructions (English)

Below we include the full-length instructions in English, with amounts in Euros. Instructions in other languages can be downloaded at *removed for anonymous refereeing*.