Average vs. Marginal Risk Aversion:

Reconciling simultaneously risk averse and risk loving behavior

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I Introduction

A vibrant literature has developed among applied economists seeking to quantify the impacts of risk on production decisions. This highly technical literature has relied on advanced econometric techniques to back risk preferences out of observed input decisions, assuming expected utility maximization. Expected utility theory attributes risk aversion entirely to the curvature of the utility function. Empirical applications seek to determine the level of curvature that best describes the input decisions. The outcomes of such estimation rely heavily on the assumption of expected utility maximization. Such anomalies as the certainty effect – where one discounts uncertain outcomes more than the probability would imply – could therefore cause severe bias in risk aversion estimates.

As highlighted by Rabin (2000) and Just and Peterson (2003), an absurd degree of curvature is required to rationalize many individuals' responses to relatively small gambles. While prospect theory is a compelling alternative explanation for decisions involving small gambles, it leaves one intriguing anomaly unexplained: why don't standard measures of risk aversion change much when moving between small gambles?

In this paper we propose an analytical and empirical distinction between *average risk aversion* – as captured by an individual's valuation of a single, stand-alone gamble – and *marginal risk aversion* – as captured by an individual's change in valuation between two gambles. After defining these concepts and deriving analytical estimation approaches for each, we use experimental data that includes individuals' valuation of gambles with different probability distributions to demonstrate the distinction between average and marginal risk aversion. We then explore the relationship between the two and discuss implications for empirical risk research.

The conceptual distinction between average and marginal risk aversion is simple. Average risk aversion is displayed when an individual's certainty equivalent for a gamble is below the expected value. Marginal risk aversion, on the other hand, is displayed when the difference in certainty equivalents for a pair of gambles is less than the increase in expected value. We derive simple measures of both types of risk aversion and apply these measures to data collected from an economic experiment conducted among Indian farmers in the state of Tamil Nadu. In this experiment, farmers stated their willingness-to-pay (WTP) for several different payoff distributions. Because farmers faced these payoff distributions sequentially, we can directly infer average risk aversion and marginal risk aversion, respectively, from their WTP for a given payoff distribution and from the change in their WTP when moving from one distribution to another. To provide nontrivial incentives, total payoffs in the experiment were calibrated so that expected earnings exceeded the local daily wage rate; several farmers earned twice this rate.

Our derived measures provide evidence that many Indian farmers are simultaneously average risk averse and marginal risk loving. This seemingly-contradictory behavior is consistent with the certainty effect and many other well known and robust anomalies in risk behavior. Importantly, it is impossible to reconcile this behavior with a single value function as suggested by expected utility or prospect theory. Given the values chosen for our experiment, such a function would need to be both concave and convex over the same range.

This empirically-relevant distinction between average and marginal risk aversion has several key implications for the estimation of risk behavior. For example, imposing a utility functional form to estimate a global utility of wealth function will produce nonsensical results when average and marginal risk aversion differs. Estimates in such a context must try to account for both local convexity and global concavity of the utility function. This may explain many of the seemingly contradictory results found in the applied literature.

II Literature Review

The *certainty effect* commonly occurs when individuals must choose between some certain outcome and at least one risky choice. Individuals behave as if the probability assigned to the sample space for the risky choice do not sum to one. Consider the following problems due to Kahneman and Tversky (1979).

Problem 1[1]: Choose between

A:	2500 with probability .33 2400 with probability .66 0 with probability .01	B:	2400 with certainty

Problem 2: Choose between

C:	2500 with probability .33 0 with probability .67	D:	2400 with probability .34 0 with probability .66

Of 72 subjects, 82% chose B, while 83% chose C. Each of these lotteries can be written as the combination of two lotteries. I will use the standard notation for a lottery, $(X_1, P_1,..., X_n, P_n)$, where X_i represents the amount of money associated with outcome i, that is realized with probability P_i. Lottery A can thus be written as $L_A = .34(2500, 33/34, 0, 1/34) + .66(2400, 1)$. Lottery B can be written as $L_B = .34(2400, 1) + .66(2400, 1)$. Lottery C can be written as $L_C = .34(2500, 33/34, 0, 1/34) + .66(0, 1)$. Finally, Lottery D can be written as $L_D = .34(2400, 1) + .66(0, 1)$. According to the independence axiom, we can eliminate the addition of common

[1] All values are Israeli sheqels.

lotteries when making choices, so that the choice between A and B; and C and D should be the same as the choice between (2500, 33/34, 0, 1/34) and (2400, 1). However, for the majority of subjects (more than 65%), the addition of common lotteries causes a change in their preferences between the two lotteries.

Behavior evident from problems 1 and 2 above have lead researchers to believe that individuals may discount the risky choices (A, C and D) below the level implied by expected utility giving an edge to the certain choice B. The certainty effect can be found when a choice between lotteries, one being a certain outcome and the other a lottery with greater expected value, is compared to the same lotteries compounded with another lottery which receives a majority of the weight. When presented with the compound lottery, the differences in probabilities for the best outcome becomes disproportionately small in the minds of individuals choosing between the lotteries. The certainty effect is pervasive and has been found by many independent studies (for another example see MacCrimmon and Larsson, 1979). Additionally, several have observed that violations tend to occur more often in choices involving probabilities near 1 or 0 (Camerer, 1995).

The certainty effect implies that individuals may exaggerate risk averse behavior when certain outcomes are available (e.g., in considering a lump sum contract) relative to when making marginal trade-offs in risk (e.g., allocating land between several crops).

The over weighting of certain events has lead many to hypothesize that individuals work to minimize expected disappointment – the feeling of loss associated with having made the wrong choice ex post, rather than maximize expected return (see Gul, 1991). This means that individuals will give up large expected value prospects when a certain alternative is available given substantial downside risk. Alternatively, the individual may give up a high value certain outcome if given the chance for a risky gamble with relatively low probability of high value outcomes. Thus the individual may use the tails of the payout distribution of risky gambles as a reference point for decision-making, similar to the notion of prospect theory.

Preston and Barrata (1948) were the first to note that individuals misperceive probabilities in choosing between risky outcomes. They ran auctions for various simple gambles – gambles in which there was a fixed probability of winning an amount of money. With regularity, they found that individuals would bid more than expected value for low probability wins (below 0.25), and under expected value for higher probability wins. The effect was robust when the experiment was run on Ph.D. statisticians and other academics highly familiar with probability measures. This effect was exaggerated when more individuals were involved in the auction. Edwards (1953) confirmed these results using individual choices instead of auctions.

This result, that small probabilities are over-weighted and large probabilities are underweighted, is one of the most robust results in risk experiments, and has formed the basis for several models (e.g., Hong's, 1983, weighted utility and Kahneman and Tversky's, 1979, prospect theory among others). Lattimore, Baker and Witte (1992) find that probability distortions seem to be dependent upon the absolute level of payoffs involved, with higher values yielding a higher fixed point. At a very rough level, Tversky and Kahneman (1992) find that the weighting function differs between gains and losses.

III Marginal and Average Risk Aversion

Identifying risk preferences using production decisions is a difficult business. Problems occur primarily because one cannot observe the probability distributions used by the decision maker (see Holt and Chavas, 2001; Lybbert and Just, 2007). These concerns are only further compounded if we assume that individuals distort the probabilities according to some arbitrary function (Just and Just, in submission). The crux of the probability weighting literature is that individuals discount uncertain outcomes in some way that does not directly affect choices between similar risky outcomes. If this is the case, estimates of risk aversion parameters assuming expected utility will be biased.

Consider the case where a farmer must allocate land between two crops (following Marra and Carlson, 1990). The farmer's decision could be written as

$$\max_{L_1 \le \bar{L}} EU\left[\Pi_1 L_1 + \Pi_2\left(\bar{L} - L_1\right) + \bar{w}\right]$$

This problem will have first order condition given by

$$E\left[U'\left(\Pi_1 L_1 + \Pi_2\left(\bar{L} - L_1\right) + \bar{w}\right)\left(\Pi_1 - \Pi_2\right)\right] = 0 .$$

To estimate the above relationship, we would need to learn the parameters of the distributions of profit for an acre of each crop as well as parameters of the utility function, using data initial wealth, the amount of land utilized for each crop, and some calculation of profit per acre. In order to find an estimable decision relationship, the above first order condition can be approximated as

$$\begin{aligned} &E\left[U'\left(\bar{\Pi}_1 L_1 + \bar{\Pi}_2\left(\bar{L} - L_1\right) + \bar{w}\right)\left(\Pi_1 - \Pi_2\right)\right] \\ &\quad + E\left[U''\left(\bar{\Pi}_1 L_1 + \bar{\Pi}_2\left(\bar{L} - L_1\right) + \bar{w}\right)\left[L_1\left(\Pi_1 - \bar{\Pi}_1\right) + \left(\bar{L} - L_1\right)\left(\Pi_2 - \bar{\Pi}_2\right)\right]\left(\Pi_1 - \Pi_2\right)\right] = 0 \end{aligned}$$

Let us suppose that land devoted to production activity 2 achieves a certain return (this could represent leasing out the land or placing it in conservation reserve). Then, the first order condition can be rewritten as

(1) $$L_1 = \frac{\bar{\Pi}_1 - \bar{\Pi}_2}{R_A \sigma_1^2},$$

where R_A is the coefficient of absolute risk aversion. If instead, the individual used a probability weighting function, the perceived mean would be diminished and the perceived variance would be lower. Let the perceived profit, and variance be given by $\bar{\Pi}_1 - \gamma_1 > 0$, $\sigma_1^2 - \eta_1 > 0$. The true decision function is given by

(2) $$L_1 = \frac{\bar{\Pi}_1 - \bar{\Pi}_2 - \gamma_1}{\tilde{R}_A\left(\sigma_1^2 - \eta_1\right)}$$

Estimating (1) when (2) is the true relationship should bias the estimated level of absolute risk aversion.

(3) $$R_A = \tilde{R}_A \frac{\left(\bar{\Pi}_1 - \bar{\Pi}_2\right)\left(\sigma_1^2 - \eta_1\right)}{\left(\bar{\Pi}_1 - \bar{\Pi}_2 - \gamma_1\right)\sigma_1^2}.$$

Thus our estimate may be higher or lower than the truth depending on the sign of the first term in the denominator. The sign of estimated risk aversion will be wrong if $\gamma_1 > \bar{\Pi}_1 - \bar{\Pi}_2$.

The above decision functions reflect the risk aversion embodied by a single decision resulting from global risk – what we will call average risk aversion. Define an *average risk aversion indicator* as $R_{aI} \equiv 1 - \frac{WTP}{EV}$ where WTP is the willingness to pay for a gamble defined implicitly as $EU\left(x - WTP + w_0\right) = U\left(w_0\right)$, where x is the risky outcome and w_0 is the initial wealth, and EV is the expected value of the risky outcome. Thus defined, this indicator is interpreted much like R_A, namely $R_{aI} > 0\ (< 0)$ indicates an individual who is average risk averting (loving). Given probability distortion, however, these two measures of risk aversion may actually have opposite signs – i.e., a risk loving individual with $R_A < 0$ may behave as an average risk averter with $R_{aI} > 0$, as illustrated by equation (2). Thus, discounting all risky choices can impact decision functions in a way that may obscure the underlying risk preferences.

Suppose now that we were to estimate using changes in production decisions when the mean of the risky distribution has changed. The models in equations (1) and (2) imply

(4) $$\Delta L_1 = \frac{\Delta \bar{\Pi}_1}{R_A \sigma_1^2},$$

(5) $$\Delta L_1 = \frac{\Delta \bar{\Pi}_1}{\tilde{R}_A \left(\sigma_1^2 - \eta_1\right)}.$$

If we estimated (4) when (5) was the true model, we would again bias our estimate of risk aversion, but now in a different way

$$R_A = \tilde{R}_A \frac{\left(\sigma_1^2 - \eta_1\right)}{\sigma_1^2}.$$

In this case, the estimate of risk aversion must have the correct sign, though the estimated coefficient will in general be biased downwards.

To derive an indicator of marginal risk aversion, we focus on changes in EV holding variance constant and changes in variance holding EV constant. In the first case, we take $\Delta WTP < \Delta EV$ as evidence of marginal risk aversion. In the second case, we take $\Delta WTP / \Delta\sigma < 0$ as evidence of marginal risk aversion. We define the *marginal risk aversion indicator* as

$$R_{mI} \equiv \begin{cases} 1 - \dfrac{\Delta WTP}{\Delta EV} & if\ \Delta EV > 0\ \ and\ \ \Delta\sigma = 0 \\ \dfrac{\Delta WTP}{\Delta EV} - 1 & if\ \Delta EV < 0\ \ and\ \ \Delta\sigma = 0 \\ -\dfrac{\Delta WTP}{\Delta\sigma} & if\ \Delta EV = 0\ \ and\ \ \Delta\sigma \neq 0 \end{cases}$$

where R_{mI} is interpreted much like R_A and R_{aI}: positive (negative) values indicates an individual is marginal risk averting (loving). Again, this should produce an estimate of risk aversion that is of the correct sign, though biased. As before,

(6) $$\Delta L_1 = \frac{\bar{\Pi}_1}{R_A}\left(\frac{1}{\sigma_1^2} - \frac{1}{\left(\sigma_1^2 + \Delta\right)}\right),$$

(7) $$\Delta L_1 = \frac{\bar{\Pi}_1}{\tilde{R}_A}\left(\frac{1}{\sigma_1^2 - \eta_1} - \frac{1}{\left(\sigma_1^2 - \eta_1 + \Delta - \Delta_\eta\right)}\right),$$

where $\left|\Delta_\eta\right| < \left|\Delta\right|$.

The previous two equations imply

$$\tilde{R}_A \frac{\Delta\left(\sigma_1^2 - \eta_1 + \Delta - \Delta_\eta\right)\left(\eta_1 - \sigma_1^2\right)}{\left(\Delta - \Delta_\eta\right)\left(\sigma_1^2 + \Delta\right)\sigma_1^2} = R_A.$$

Such behavior is important in practice because the fixed effects of risk enter into the standard first order conditions as in (2). Thus, the common approach using first order conditions will produce estimates that are not predictive of how behavior will change given changes in the parameters of the distribution of profits or other production characteristics. Rather, these estimates will be highly biased and potentially imply risk averse behavior when in fact the underlying behavior is risk loving on the margin. Alternatively, estimating using observed changes in behavior, though it will not allow us to identify the distortion of probabilities, should lead us to operationally more accurate predictions of farmer behavior.

IV Data

This article uses data from the Salem and Perambalur districts of Tamil Nadu state, India (see figure 1). These data were collected with local support from Tamil Nadu Agricultural University and funding from the Agricultural Biotechnology Support Program (USAID-Cornell University). Ten enumerators surveyed 290 households in three Perambalur villages (Annukur, Pandagapadi, and Namaiyur) and three Salem villages (Vellaiyur, Kilakku Raajapalayam, and Kavarparnai).

The team collected data in two parts. In the first part, enumerators administered a detailed household questionnaire focused on farmers' management decisions, valuation of seed traits, risk exposure and wealth. In the second part, the team conducted experiments with farmers to elicit their valuation of hypothetical yield distributions. Farmers earned money (Rupees (Rs)) according to their performance in the experiment.

The experiment consisted of a series of hypothetical farming seasons. At the beginning of each season, farmers were offered a 'seed' with a known Rupee-payoff distribution. This distribution was explained simply and repeatedly and shown graphically in order to facilitate farmers' understanding of the payoff distribution implied by a given 'seed.' The distribution of a particular 'seed' was represented by 10 chips in a small black bag. There were three colors of chips, each representing a 'harvest' payoff: blue (high), white (average), and red (low). The distribution was modified by changing the proportion of blue, white and red chips in the bag. Farmers' valuation of the seed was elicited using an open-ended question and the well-known Becker-DeGroot-Marschak (BDM) mechanism (Becker, DeGroot and Marschak 1964). As shown in figure 2, we focus on four payoff distributions from the experiment: a benchmark *base* distribution (B), a *high* distribution with a higher mean payoff (H), a *low* distribution with a lower mean payoff (L), a *stabilized* distribution with lower variance (S). For the purposes of this paper we ignore the truncated distribution shown on the right. Figure 2 shows the marginal probability distributions and the expected value (EV), standard deviation (σ) and skewness (sk) for each of these distributions.[2] Every farmer valued each of these payoff distributions several times, first during practice rounds then in a final high stakes round.

[2] These simple typological distributions where chosen to facilitate farmers' understanding of the experiment. We used simple pictures like those in figure 2 to capture each distribution and explain the experiment to farmers.

To control for learning and ordering effects, all farmers started and ended with the benchmark distribution B (denoted B1 and B2, respectively), between which distributions H, L, S, and T were randomly ordered (see Lybbert 2004 for more details about the experiment). These data have been used elsewhere to assess poor farmers' valuation of pro-poor seeds and to explore the strengths and weaknesses of field experiments as a methodology in conducting policy-relevant research (Lybbert 2006).

V Analysis

In this section, we analyze the average and marginal risk aversion indicators defined above. We first present descriptive statistics based on these indicators, then compare the two indicators in an effort to detect deviations and patterns between average and marginal risk aversion, which are implicitly assumed to be the same whenever a single globally concave utility function is invoked.

According to Table 1, generally a majority of individuals in our data are average risk averse according to our indicator R_{aI}. The one exception is for gamble L, which was the only one that involved losses. This may result from simple anchoring and adjustment mechanisms, whereby individuals anchor on their WTP for the base gamble, and then fail to adjust sufficiently up or down when valuing the alternatives. In the experiment, we presented the B distribution as the baseline distribution (as explained above), and all other distributions were presented sequentially as variations of this baseline distribution. It is therefore natural to compute marginal risk aversion based on how a distribution and WTP changes relative to the B distribution. This behavior is similar to those supposed by prospect theory. In this case, however, there is a reference gamble rather than a reference point. From Table 1, the percentage of marginal risk averse individuals, based on R_{mI}, is shown for these gamble pairings. In all cases, fewer individuals were marginal risk averse than were average risk averse. In the case of the S distribution, a majority of individuals are *average* risk averse, and a majority is simultaneously *marginal* risk loving.

Next, we use kernel regressions to analyze whether there are any distinct patterns in differences between average and marginal risk aversion as captured by our indicators. Specifically, these regressions use an Epinechnikov kernel to map the nonparametric relationship between marginal risk aversion for (*i*-B*j*), *i*={H,L,S} and *j*={1,2} and average risk aversion for distributions *i* and *j*. These regressions are shown in Figures 3 and 4 and include a scatterplot of these indicators. Based on the definitions of our indicators R_{aI} and R_{mI}, the positive (negative) quadrant of these graphs contains all individuals who were risk averse (loving) both on average and at the margin. The other quadrants contain individuals who were simultaneously risk averse and risk loving.

The general pattern of behavior is consistent with our notion of a reference gamble. In this case, we see that marginal risk aversion is negatively related to average risk aversion over the base gamble, but positively related to average risk aversion for all other gambles. This is evidence that the individuals' WTP for all gambles were anchored on their WTP for the base gamble. Moreover, the relationship of marginal to average willingness to pay for the non-reference gambles is surprisingly a relatively stable relationship, illustrated by the nearly straight curves resulting from the kernel regression. Further, the regression curves in the three right hand side panels are of nearly the same location and slope, though the ranges of average risk aversion on the horizontal axis is different for each gamble. If this relationship holds true more generally, estimation of marginal and average risk aversion resulting from a pair of gambles could be predictive of the measures of risk aversion over a wide range of gambles.

VI Discussion

In this paper we differentiate between marginal and average risk aversion. Marginal risk aversion embodies the changes in behavior observed when the underlying gambles change. Average risk aversion is embodied by the behavior observed for a single gamble. Empirical work has focused solely on average risk aversion, and its impacts on production and other behaviors. Well documented behavior anomalies suggest that average risk aversion measures will not be predictive of behavior when underlying risky choices change. This may result from probability weighting, or from reference based behavior. Rather, we suggest that marginal risk aversion measures will be more robust to estimation bias, and have a greater ability to predict behavioral changes. The results of our experiment confirm strong differences between marginal risk aversion and average risk aversion, depending primarily on how the gamble is adjusted from a reference gamble. We find remarkable regularity in the relationship between marginal risk aversion and average risk aversion across a set of several gambles. Average risk aversion measures display unreasonable variation across gambles, undermining the researchers ability to predict behavior in one gamble from that in another relying solely on average risk aversion measures. We conclude that future empirical work should focus on obtaining measures of marginal risk aversion, potentially making use of the widening array of matching techniques from the econometric literature. Such estimates stand a greater chance of capturing general (rather than idiosyncratic) behavior.

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Figure 1 Map of surveyed villages in Salem and Perambalur districts of Tamil Nadu (TN), India (India map courtesy of www.theodora.com/maps, used with permission)

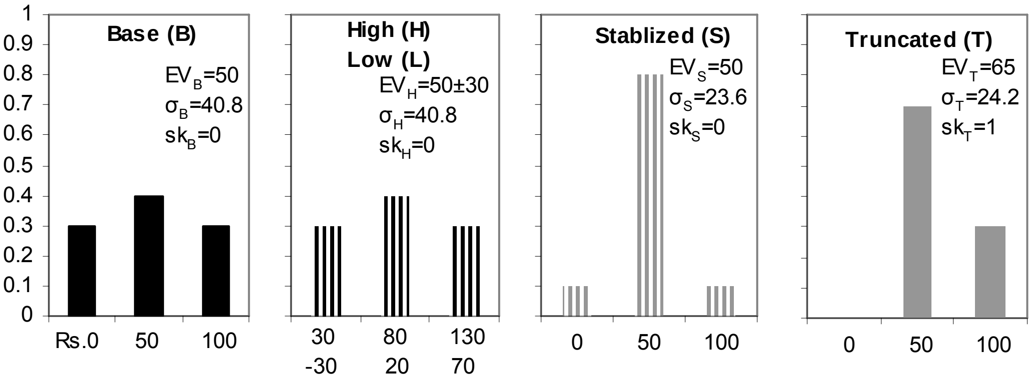

Figure 2 Marginal probability distributions for distribution types used in experiment (payoffs in Rupees (Rs) on *x*-axis)

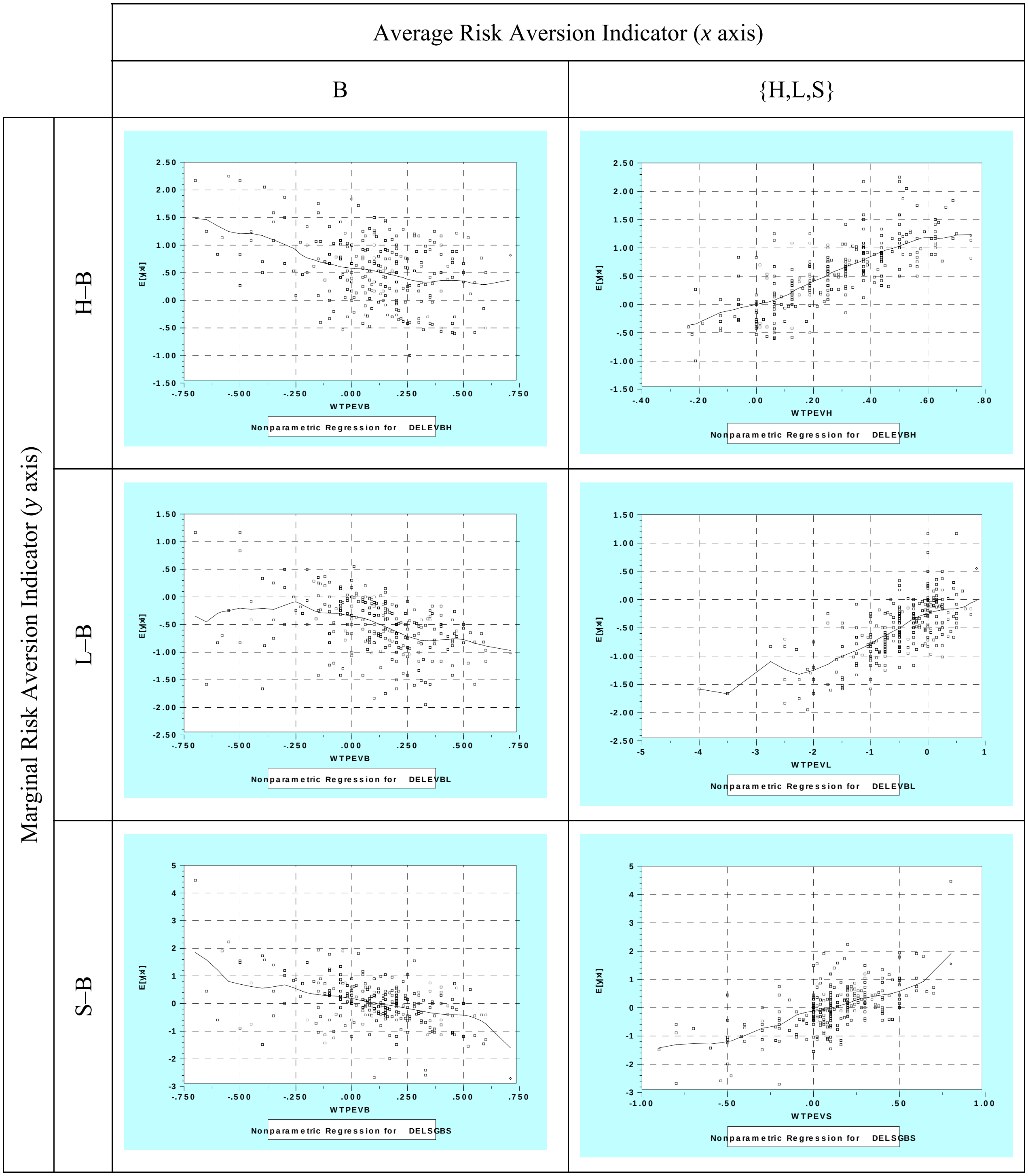

Figure 3 Kernel regressions of marginal risk aversion indicator (R_{mI}) relative to distribution B on average risk aversion indicator (R_{aI})

Table 1 Percent of individuals who are average and marginal risk averse

Distribution	% Average Risk Averse (R_{aI}>0)	Δ Distribution	% Marginal Risk Averse (R_{mI}>0)
B	69%		
H	89%	**H - B**	81%
L	23%	**L - B**	10%
S	74%	**S - B**	49%
N=	290		290