Whither Risk? Dynamic Measurement of Risk Preferences with Application to Gender Differences Between Children and Adults

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Abstract

We present the results of a novel experimental measure of preferences under risk, and compare the preferences of children and adults. Our data allows to contribute to the 'nature vs. nurture' debate of the origins of gender differences in attitudes towards risk (and we show it has a clear aging component), as well as to propose a novel dynamic measure of risk preferences with feedback about the quality of own choices. Specifically, we develop and estimate a structural model of preferences under risk, which allows to disentangle risk attitudes per se from the expectation about own skills (aspiration levels), which we model as dynamic Bayesian process. Resulting estimates suggest that static measures which fail to account for aspirations result in overestimation of risk tolerance, especially among the adults.

1 Introduction and problem statement

Risk aversion is traditionally viewed as one of the key behavioural measures of individual preferences in uncertain environments, typical of most economics and real-life context. In this paper, we claim that the meaning of risk preferences, and especially their measurement in economics so far have been predominantly focused on only one aspect of risk preferences, leaving aside the other, which is not less important in practice. Traditional experimental measures ([4]; [19]; [21]; [1]; see [10] for a survey of methods) are limited to what may be called *prior risk*. As a prototype real-life story, consider a sailor on the sea shore who decides whether to undertake a boat trip on a windy day and unsettled sea or not. This decisions should rationally be made upon weighting the benefits of such a trip (be these pleasure from sailing, amount of fish caught etc.) against prior estimates of risk based on previous experience and knowledge of own boat and skills. In such contexts, risk preferences mean exogenously predetermined individual predispositions to expose oneself to situations with unknown outcomes, which may be described by objective or subjective probability distributions, perceived by the subject in a mathematically correct way (as finitely or countably additive probability measures). This definition implicitly assumes that subjects possess developed probabilistic intuition, which is itself a fundamentally correct representation of subject's perception, and drives one's action under risk. This approach lies in the background of classical measures of risk attitudes involving exogenously predetermined lotteries, which may be presented to the experimental subject in relatively more abstract form (as discrete probability distributions), in graphical form (as pies or areas), or in gamified and interactive form, as in BART [18] or BRET [22]. These latter are perhaps most intuitive, but still bear on and measure this same prior intuition of what is risk and how does one behave towards it.

However, in real-life decisions people most often have to exhibit other kind of risk preferences, which arise in repeated interaction with uncertain environment, and emerge along with their learning and mastering of that environment itself. As a prototype example, consider a newbie car driver who learns how to drive her car. At first, it is hardly clear for her what kind of driver's decisions are too risky for her, and which ones are not: she simply has not enough experience. But she has to drive anyway, and make some decisions, to the best of her understanding of what is safe enough for her to do, given her perceived competences and abilities. Upon these decisions, she receives some feedback — in the form of successful or unsuccessful takeovers, turns at particular speed, road behaviour and driving style etc. It is only gradually that she learns these skills, and simultaneously develops her attitude to risk in this environment. In such cases, risk preferences are developed along with her abilities and confidence, which are also updated in the light of her experience. These preferences towards risk are learned only gradually, together with understanding of one's own abilities to cope with that environment, be it car driving, manual work (hammering, sawing, woodcutting etc.), sports, bodycare, business decisions, trading in financial markets etc[1]. We call these risk attitudes *dynamic* or *Bayesian*, using this last term in a somewhat loose sense. We do not necessarily claim that learning one's preferences towards risk have must follow an optimal path stipulated by Bayesian posteriors given the sequence of evidences about one's past successful or failing decisions. However we do believe that one's risk preferences in these uncertain environments are proportional to that sequences of experiences (successes and failures) — in other words, subjects respond to these experiences in an incentive compatible way.

In this paper we propose a framework for the analysis of dynamic (Bayesian) risk attitudes in closed-loop settings using a novel decision task presented on Figure 1. The task is very simple, which makes it suitable for experimental subjects of all ages (our youngest participant was 3 years old) who have no physical or neural difficulties with

[1]Further examples include student cheating at an exam, who is likely to reconsider the intensity of subsequent cheating depending on whether the first attempt has been successful or not; tax evader who adjusts his avoidance strategy conditional upon being monitored last time; entrepreneur who opens her n-th business, trying to avoid decisions that have been proven wrong in one's previous attempts; traveler who, once robbed in a particular area of the city, tries to choose other routes in the future, etc.

motor tasks. Our subjects face an identical sheet of A4 paper which has one of its angles split into several (in our case, eight) sectors, diminishing in size from the lower right corner towards the center of the sheet. Subjects have to put a spot with a pen on one of the eight sectors of their choice, close their eyes and bend out their head, raise the pen at about 25 cm above the table, and put it down to the piece of paper, trying to hit the same *sector* they have targeted, still keeping closed their eyes. Obviously the higher (narrower) is the sector targeted, the higher are chances to miss it, so the higher is risk.

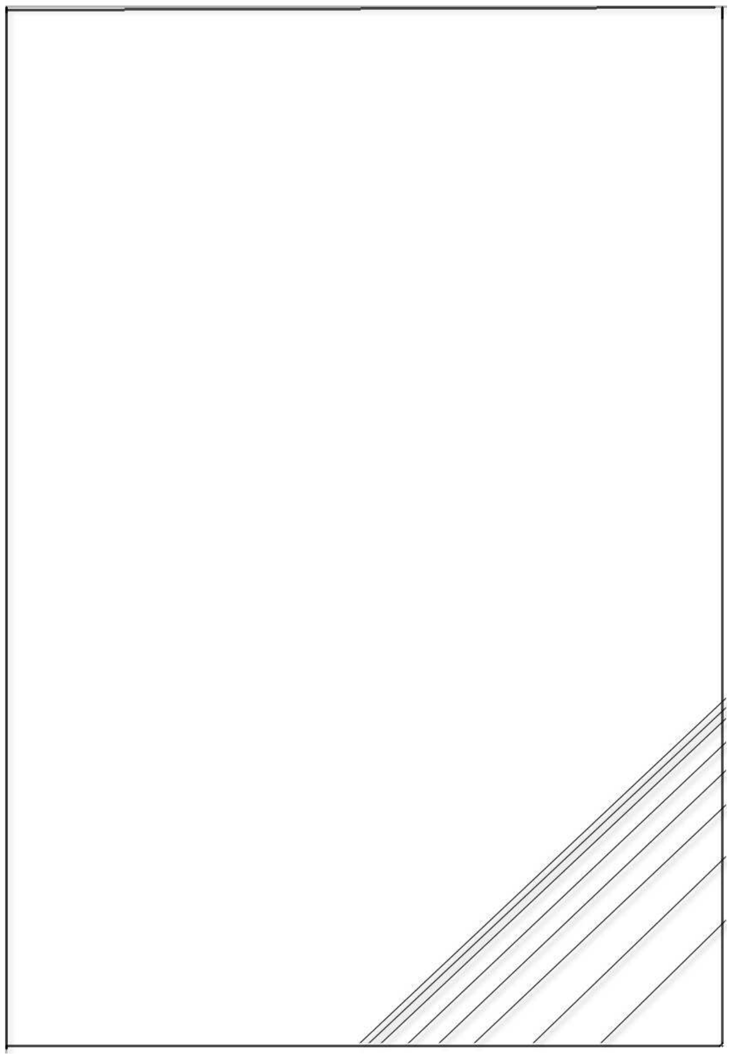

Figure 1: Experimental field

After the first hit, participants have to put the number of attempt next to the target and the hit, putting the last number in a circle, and proceed with the next round, following exactly the same rules. Altogether, participants had 5 attempts, each time observing the outcomes of all previous trials (success or failure), and hence being able to adjust their decision (target sector) depending on the path of past realisations. This task is very simple, and can be easily explained to participants of any age and experience, including those who are completely unfamiliar with probability theory, and even numerically illiterate. We have made use of that to contrast behaviour of adults (university students) with that of adolescents (high school students) and children: our youngest participants[2] were aged 3, and our setup has no age limit, inasmuch as subjects have no motion neural problems.

Using participants' age, as well as types of reward (money and grade points for the students, fruits for children) we analyse the effect of age and incentives on people's preferences towards risk in this setting. This contributes to the 'nature vs nurture' discussion on pre-programmed vs socially constructed gender differences in risk preferences. Young children have clearly less exposure to gender stereotypes than adults, and hence their behaviour towards risk tends to be driven by natural predisposition to a much higher extent than that of the adults. Indeed, in line with most of the literature, we find that adult females are more risk averse than males, which is especially well-pronounced in the very first (intuitive) attempt, when people were not able to gain any experience[3]. No similar difference is observed among children. Further, we find that adult females are systematically more reactive than adult males to the sequences of successes and failures — something which is not observed among children. These conclusions in our novel dataset suggest that gender differences in attitudes towards risk are not innate, but develop as children grow up[4].

Another contribution of the paper is its direct measure of dynamic, or Bayesian risk, and in particular, separation of preferences towards this type of risk from own aspirations to cope with the problem in question. Indeed, in our experiment, as well as in all real-life examples discussed above, each decision results from a combination of two factors: preferences towards risk r and beliefs in own abilities to cope with the problem of a given complexity, or own aspiration level θ ([20]). In light of this discussion, throughout this paper we speak interchangeably about 'difficulty' and 'riskiness' of choice being made (higher sector chosen in our experiment), but we reserve 'risk preferences' and 'risk attitudes' to the narrow definition in the sense of parameter r. Actual choice is the maximand of composite utility function under risk which depends on two separate parameters: $U(x, p|r, \theta)$, where x and p are outcomes and probabilities. We adopt and propose an instrumental way to estimate and disentangle r and θ using a

[2] In [16] the youngest participant was 5 years old, and it is practically impossible to measure risk attitudes of yet younger children using their technique

[3] Due to the novel character of our experimental technique, it is natural to claim that no subject had any previous exposure to that kind of task, and hence has to rely on intuitive, prior and pure preferences.

[4] Our present treatments, however, do not warrant causal attribution of these differences among adults to *nurture* rather than *nature*: gender differences in risk preferences among the adults may be caused, e.g., by hormonal responses over the perturbate period rather than rising social and cultural influences and embeddedness along the same path

simple model of general learning dynamics which uses incoming evidence to update self-representation of one's ability to perform a particular decision task. Risk attitudes are then measured as the difference between the level of difficulty of the task chosen at the final stage of the learning process and the updated level of abilities (aspiration). Resulting estimates are conditional on the model specification; using the most natural of these, we contrast our Bayesian risk preferences to the overall pattern, and compare them to measures collected in the traditional way (e.g. as multiple price list lotteries). These last measures are consistent with the usual finding: adult males are slightly, but systematically more tolerant to risk than females. However, our Bayesian model attributes most of these preferences to updated aspiration levels: males are significantly more ambitious than females, which difference is more pronounced among the adults than among the children. This aspiration effect outweights proper attitudes to Bayesian risk: results of Monte-Carlo simulations suggest that adult females and males do *not* differ in tolerance to dynamic risks, whereas boys are systematically more risk seeking than girls (and than men; girls' preferences to risk do not differ from that of adult women). This claim has obvious implications for the literature on gender differences in risk preferences (Cameron e.a., 2001 etc) as well as ambitions and competitiveness ([23]): women are actually more inclined to take risks than men, but have even lower aspirations. Further, this effect seems to be present even among small children, yet tends to increase with age.

The rest of the paper is organized as follows. After a brief review of the modern literature on risk preferences in section 2, we present the main descriptive statistics of our experiment in section 4, and the model that disentangles aspirations from risk preferences — in section 5. Section 6 concludes by stating some directions for further research.

2 Related literature

Despite several controversies, researchers in the field convene in the set of (mostly) incentivised measurement techniques which are widely used in economic experiments (see, e.g., [**?**] for a concise summary). Researchers traditionally, albeit rather tacitly, assume that these measures should remain valid indicators of risk attitudes in other tasks, such as experimental games, survey questions, and real-world phenomena, be it purchases of insurance, hazardous driving or financial markets [3]. In practice, however, both laboratory and field studies have been focused on prior risks, not on the dynamic ones. Most of the laboratory studies have used either self-reported attitudes, which solicit willingness to take risk in various contexts, or motivated measurements. These latter may be further subdivided to various methods, such as Investment lotteries (Gneezy and Potters, 1997): "Of a windfall gain of 1 million, how much you would be willing to invest in a business venture which would result in doubling the invested amount or complete perish of investment with equal probabilities?"; Dominant pricing ([4]; Revealed ([29]) and Structural estimation of utility function parameters ([2]; [11]); Tradeoff method ([1]). Implied risk aversion ([14]) and Multiple price list ([19]) have been proven the most popular in applied work (see Figure **??**), largely because of their simplicity and intuitive appeal, which also made them highly suitable for crosscultural comparisons ([30]; [17]). Some authors have used lab techniques in more realistic, lab-in-the-field contexts. Thus, [31] used the Gneezy-Potters techniques in a 15-day experiment compared risk tolerance of online investors to that of lab investors, and [13] incorporated incentivised risk preferences' elicitations in nationwide survey studies. Further measures of risks involve financial decisions ([24]) and sports competition ([7]), where women are shown not to take risky opportunities in pole vault and high jump, even if it is beneficial for them.

All these methods solicit statement of preferences over risky lotteries which, in one way or another, ask subjects to state their preferences towards lotteries — uncertain prospects, given by outcomes and probabilities. This statement in itself assumes numerical literacy, and hinges on intuitive understanding of probabilities as measures of random events. In contrast, gamified methods, such as BART (Baloon Attitudes to Risk Test, [18]) and BRET (Bomb Risk Elicitation Task, [22]) are yet more intuitive, although formally speaking, they deal with uncertainty rather than risk. Hence, all these studies, as argued above, are limited to what we call preferences for prior risks: they all aim at eliciting one's attitudes towards a description of risky situation, which description is supposed to be prior, or based on previous experience. This specification may lead to limiting predictive abilities, especially when the risky situation in question is likely to be new to the subjects, as well as to some theoretical paradoxes, such as the Rabin ([26]) calibration theorem, which shows that that conventional risk aversion coefficients in CARA, CRRA or their generalizations, such as expo-power utilities ([25]) turn out to be unrealistically large.

Figure 2: Typical lotteries for Implied Risk Aversion

Table 1
The Eckel and Grossman measure.

Choice (50/50 Gamble)	Low payoff	High payoff	Expected return	Standard deviation	Implied CRRA range
Gamble 1	28	28	28	0	$3.46<r$
Gamble 2	24	36	30	6	$1.16<r<3.46$
Gamble 3	20	44	32	12	$0.71<r<1.16$
Gamble 4	16	52	34	18	$0.50<r<0.71$
Gamble 5	12	60	36	24	$0<r<0.50$
Gamble 6	2	70	36	34	$R<0$

Figure 3: Typical lotteries for Multiple Price List (Down)

TABLE 1—THE TEN PAIRED LOTTERY-CHOICE DECISIONS WITH LOW PAYOFFS

Option A	Option B	Expected payoff difference
1/10 of $2.00, 9/10 of $1.60	1/10 of $3.85, 9/10 of $0.10	$1.17
2/10 of $2.00, 8/10 of $1.60	2/10 of $3.85, 8/10 of $0.10	$0.83
3/10 of $2.00, 7/10 of $1.60	3/10 of $3.85, 7/10 of $0.10	$0.50
4/10 of $2.00, 6/10 of $1.60	4/10 of $3.85, 6/10 of $0.10	$0.16
5/10 of $2.00, 5/10 of $1.60	5/10 of $3.85, 5/10 of $0.10	−$0.18
6/10 of $2.00, 4/10 of $1.60	6/10 of $3.85, 4/10 of $0.10	−$0.51
7/10 of $2.00, 3/10 of $1.60	7/10 of $3.85, 3/10 of $0.10	−$0.85
8/10 of $2.00, 2/10 of $1.60	8/10 of $3.85, 2/10 of $0.10	−$1.18
9/10 of $2.00, 1/10 of $1.60	9/10 of $3.85, 1/10 of $0.10	−$1.52
10/10 of $2.00, 0/10 of $1.60	10/10 of $3.85, 0/10 of $0.10	−$1.85

Finally, we need to mention the literature on age and gender comparisons of risk attitudes. Age effecs are explored much poorer, and mostly in psychology, while gender effects are studied extensively [8]. In the standard settings, higher tolerance to risk among men than among women is well-acknowledged in the literature ([14]; [6] [12]), although there are some opposing results ([9]). Some studies question significant differences in risk preferences for self-reported ([28]) and laboratory ([**?**]) contexts. Related to these are the effects of social interactions: in an influential paper, Niederle and Vesterlund ([23]) have shown that women are significantly less competitive than men, even controlling for risk preferences. At the same time, there is evidence that women are may be more competitive in all-women than in mixed environments ([5]).

3 Experiment

Unlike the previous studies, our experiment has been explicitly framed to measure Bayesian risk attitudes. It has been conducted in various audiences, over 2012-2014 academic years in the city of Moscow, Russia, and its vicinities. Subjects were endowed with a standard pen and a playfield as presented on Fig.1 — a sheet of A4 paper with ruled lines, and no other marks on it. They were instructed to put a spot in any of the 8 sectors, close their eyes and bend back their head; then raise a pen in their working hand at about 25 cm above the table, and put it back, aiming at the same spot. The move is deemed winning if the person succeeded to hit the same sector, without rewarding proximity to target spot. Each winning hit brings to subject the number of points equal to the number of sector that has just been successfully targeted, 1 being the largest (lower right corner) and 8 the smallest. Subject is then asked to put the same number of attempt next to the target and the trial (1 through 5), putting the last number in a circle. All this has been communicated to the subjects at the very beginning by the experimenter in oral form.

Sessions were conducted in five different treatment conditions, altogether 324 subjects. Participants of the experiment represented two samples: children and adults. Children were pupils of several kindergardens in Moscow city, altogether 52 children aged 3-8, of which 52% were female. As incentives for them we have used fruits (number of grapes), awarded according to the number of points accrued to the successfully hit sectors. Students were recruited from various audiences in Moscow city and all Russia, who played in in 4 separate groups:

Money: students who received 10 roubles per sector that has been point earned (about 40 euro cents at the moment of the experiment). This sample consisted of 21 people (48% female).

Material prizes: fruits or stationery (calendars, pens, notepads, in accordance with points earned — altogether 150 people, 51% females.

Moral: High-school students aged 15-17, 127 people, 61% females, played for interest (or 'for fun').

Course grades: 35 students people, 69% females, who could theoretically receive up to 10% for their course grade (in an impossible case of getting 5 out of 5 attempts at the highest sector number 8, linearly downscaled for lower performance.

Average age of children were 4.9 years, average age of students — 20.25 years, average age of high-school students - 16.1 years (pre-terminal grades 9-11 of the Russian secondary education). For the purposes of our analysis we use only data for students who played for real money and material prizes, and compare it to that of children.

Our experimental setup is novel to the literature — hence, it seems pretty obvious that none of our subjects took place in it before. However, the experiment itself was easy (and even fun) to subjects of all cohorts: on average, it took about 5 minutes to explain how to proceed and around 10 minutes to complete the whole task. Because it was very easy, no written instructions have been handled to the subjects, and no trial attempts were provided. Some subjects have attempted to 'train' themselves through one or more dry runs (hits of the playfield without leaving marks on them), which was not disallowed. The experimenters were around all the time during the experiment to ask questions, help participants to mark their targets and hits, and prevent possible cheating (opening eyes during the attempt etc.). In children session, the experimenter was helping the participants personally in each of their attempts, but subjects were left to freely decide what to do in the game.

4 Results

4.1 Descriptive statistics

Mean choices and success rates over all trials for all four groups are illustrated on Figure 4. As clearly follows from that figure, distributions of the outcomes are basically similar to commonly observed trends. On aggregate, adult players exhibit unimodal choices, with slightly larger spread for males. Success rates are uniformly decreasing with difficulty for adults (both males and females). For children, the pattern is more hectic, without clear trends. However, judging by the statistical tests, males make slightly riskier choices than females, which tendency is visible for both adults and children, and marginally significant: the corresponding WMW test statistic for children is $z = -1.91$ ($p < 0.055$), for adults, $z = -1.79$ ($p < 0.073$). Similar conclusion is also true in another direction: choices of adults are typically riskier than those of children, for both males and females (see also Figure 5).

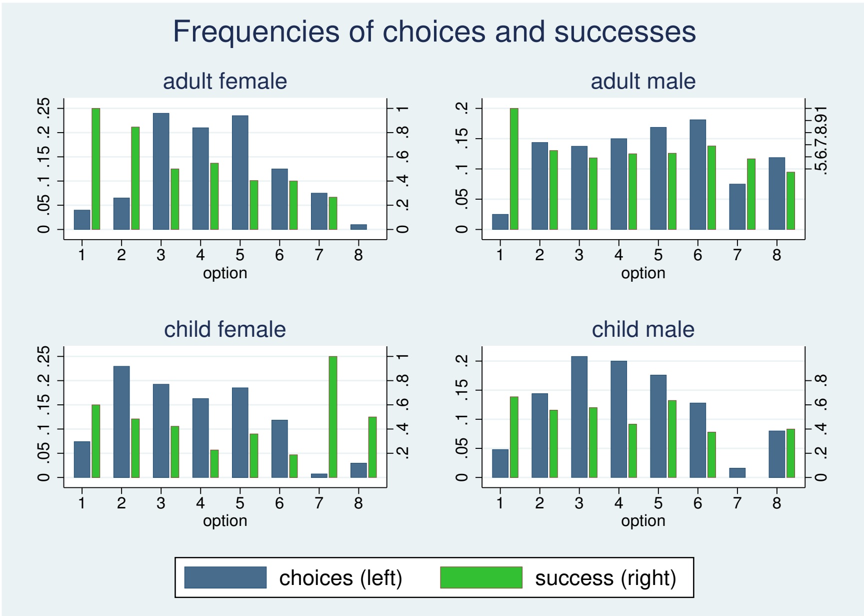

Figure 4: Distributions of decisions and success rates

Hence, we may formulate

Result 1 *Riskiness of average choices over the experiment is systematically lower for females than for males, especially among the adults and less so for the children.*

Result 1 is quite expected, as it goes in line with all traditional measures of prior risk, just using different instrument. In particular, upon conventional reading, our measurement also would imply that adult females are significantly more risk averse than males as presented on Figure 5, left panel; whiskers correspond to 0.95 confidence intervals). Further, inasmuch as risk preferences of children do not significantly differ across genders, one might be tempted to conclude that aging is an important factor of gender differences in risk aversion: higher riskiness of males is a matter of personality development (nurture rather than nature). All these conclusions, however, would be premature in our setup, because in our dynamic settings, risk preferences are elaborated alongside with the skills to solve the task, and self-perception of these skills. Specifically, if we restrict attention to the first trials only, when subjects make their first risky move in this environment (Figure 5, right panel) — the above tendency breaks down.

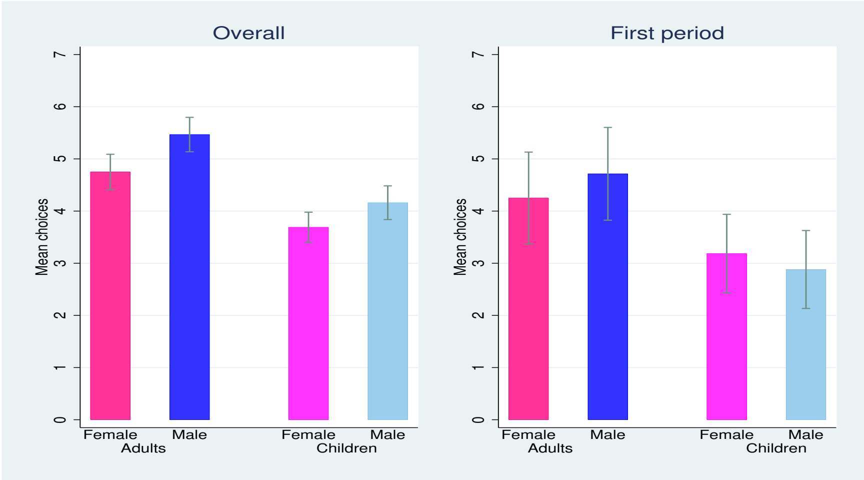

Figure 5: Mean decisions by treatments and groups

Here, decisions look less systematic, and none of the gender differences is significant in any direction at first. This observation is consistent with the idea that aging results in more challenging choices, and in connection with the previous figure, also suggests that the learning patterns of adults and children are different — result that we further elaborate in the next subsection.

4.2 Strategies

We begin by considering subjects' reaction on previous experience. Figure 6 shows the distributions of mean adjustments of decisions following success (left) and failure (right) of the previous trial for the whole sample, and 7 does the same by treatment categories (females vs. males and adults vs.children). Both graphs are based on the mean adjustments of individual players for each subcategory of participants.

As is obvious from the pictures, changes of choices are not very often: median increase of decision after success is just 0.5, and it is zero after failure. After success, the main response pattern is a mild increase in decisions. After failures, the picture is less homogeneous, with one peak above and one below zero. Breakdown by treatments in Figure 7 reveals the reasons for that, and Table 1 reports summary statistics, with significant differences highlighted in colors as described below. Successes result in increasing the difficulty of choice on average by about 0.5 points at a scale of 1 to 8, except for male children, for whom this is larger (0.88). In fact, the only group significant contrast here is that between adult males and boys: the latter tend to increase their bids to a significantly larger expect than adult men (WMW test values $z = 2.26, p < 0.023$, here and below, colors correspond to the respective comparisons in Table 1).

At the same time, bids decrease following failure is typical of adults, but not of children, who, on average, keep the level of difficulty intact (girls) or increase it (boys).

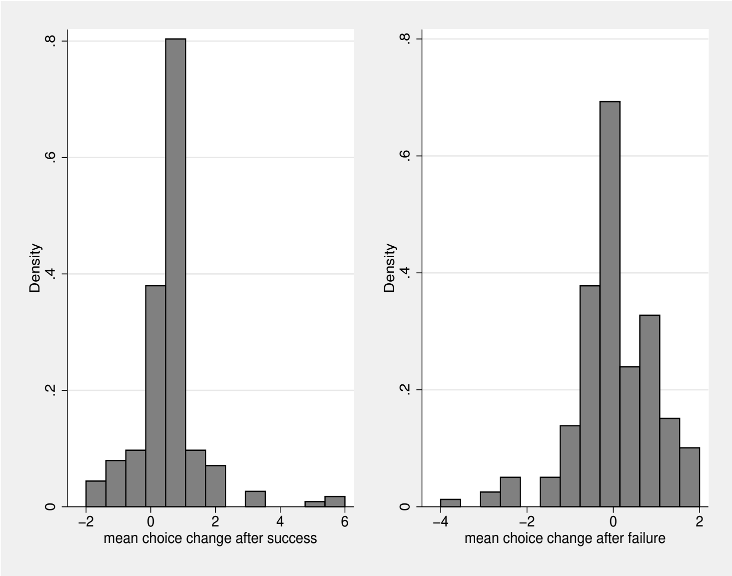

Figure 6: Decisions following successes (left) and failures (right)

Differences in decreasing strategies are not significant across genders for adults, but are so for children (underlined, $z = 2.57, p < 0.01$). Significant are also differences between children and adults for both males ($z = -3.26, p < 0.0008$) and females ($z = -2.22, p < 0.026$). This implies that boys again are more aggressive under failure than girls are. Adults, by contrast, reveal more conservative behaviour: unlike children, their failures lead to decreasing the level of challenges rather than increasing it, as some boys tend to do. So, we may state the following

Result 2 *Boys tend to take significantly more challenging decisions following success, and less challenging decisions following failures than girls do. Adults of both sexes take less challenging decisions following failures.*

We conclude that successes, on average, have larger effect on subsequent behaviour than failures: mean increase of the level of difficulty amounts 0.5 for all cohorts, and is even larger for boys, while mean reaction to failures is around zero, but is generally more heterogeneous. After unsuccessful attempts, adults of both genders become more cautious and decrease the level of challenge on average by about 0.25. Children, by contrast, behave more optimistically: girls, on average, make another attempt at the same difficulty level, while boys tend to increase the stakes, revealing the most 'bullish' behaviour of all four cohorts. Altogether, this shows that learning from own failures is typical of adults, but not well-expressed among children.

These conclusions are reinforced by the average number of decisions to change strategy following successes or failures, without considering their signs. Table 2 shows that adult males significantly more often change strategies after successes than after failures, whereas females do so in the same proportions. Boys more often change their

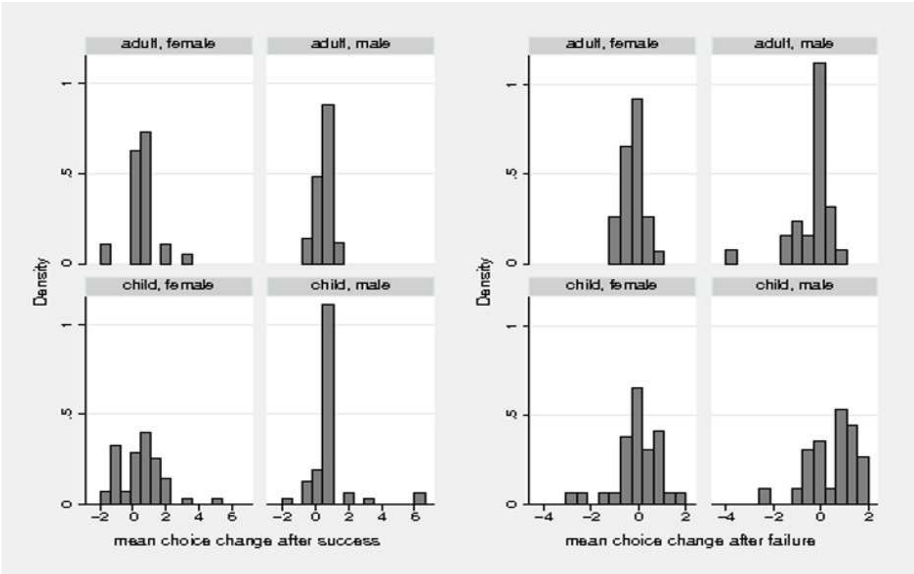

Figure 7: Decisions following successes (left) and failures (right), by treatments

choices following successes, while girls — following failures, but this last contrast is the only one that is not significant statistically ($\chi^2 = 5.93, p < 0.204$), marked in italics; all other contrasts are significant, and most often highly so. Fairly comparable results are shown on Table 3, which shows frequencies of keeping the same strategy. After Success, women adjust their strategies significantly more often than men. Girls do it somewhat more often than boys, but this is only marginally significant. After Failure, women adjust their strategies significantly more often than men, while girls and boys do so at the same frequency.

Finally, Figure 8 shows that boys tend to increase their bids no matter what after failure all over the range (trials 2-5), whereas adult males tend to be very cautious after failures towards the end only (trial 5). No clear trends are visible among females, and there are no regular tendencies either after successes, for any cohort.

Table 1: **Strategy changes after Successes and Failures**

	after Success			
	Female		Male	
statistics	Adult	Children	Adult	Children
frequency	31	45	57	51
mean	0.52	0.51	0.47*	0.88*
st.dev.	0.97	1.33	0.49	1.27
	after Failure			
	Female		Male	
statistics	Adult	Children	Adult	Children
frequency	33	63	27	49
mean	−0.21*	0.00*(**)	−0.30***	0.49***(**)
st.dev.	0.45	1.01	0.95	1.07

Table 2: **Mean number of strategy changes following Successes and Failures**

		female	male
Adults	after Success	*1.55*	2.39
	after Failure	1.44	0.71
Children	after Success	*1.46*	1.97
	after Failure	1.90	1.75

Table 3: **Proportions of unchanged choices following Successes and Failures**

	after Success				after Failure			
	Adult		Children		Adult		Children	
statistics	female	male	female	male	female	male	female	male
freq.of same	0.19	0.33	0.22	0.09	0.34	0.50	0.21	0.20
st.dev.	0.39	0.47	0.42	0.30	0.47	0.50	0.40	0.40
χ^2	5.67***		2.79*		4.51**		0.000	

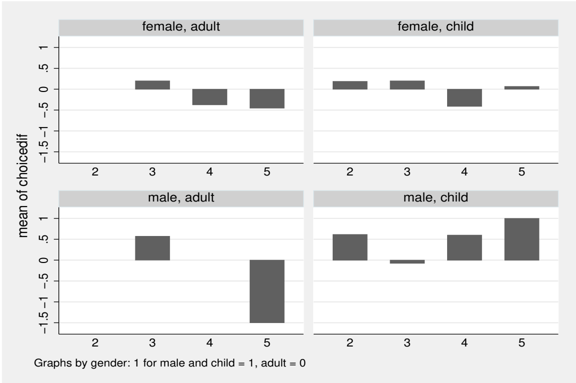

Figure 8: Mean changes in decisions following failures, by trials

One might speculate over the origins of these differences changes, which is not necessarily an easy thing, not least because the experimental technique allows for some flexibility in behaviour, not least because motor abilities of subjects can be different. Nevertheless, subjects' reactions to one's successes and failures is hard data, and the evidence reported in this subsection is based entirely on it. Taken together, it implies that there are substantive and systematic differences in one's strategies under risk depending on successes and failures, i.e. dynamic updating of one's decisions in risky settings that are novel to the subjects. This conclusion stresses the importance of learning dynamics when dealing with Bayesian risk, which learning unveils quite differently for men and women, boys and girls.

4.3 Statistical evidence

We now proceed with statistical analysis of the determinants of risky choice. Table 5 contains estimates of the various linear models; ordered models of sectors of choice yield qualitatively similar results.

The first model is OLS with individual-clustered standard errors based on pooled data. Subsequent models are random errors panel data model which accounts for individual-specific and time effects on choices, and hence is more accurate. As explanatory variables we use an objective measure of probability of success, defined as the proportion of each sector in all area of successful hits. These proportions for each sector, starting from the lower right corner, are provided in Table 4, and labeled 'Risk level' in Table 5. Alternative, equiprobable estimates of probabilities are tantamount to constant, and hence are qualitatively equivalent to the model without this variable. Results of these estimates are again qualitatively similar.

Other explanatory variables include choice in the first period ('First period'), as capturing preferences in the new environment without any feedback as to own abili-

Table 4: **Shares of sectoral areas (in $)**

Category	1	2	3	4	5	6	7	8
Probability	36.69	18.82	12.48	9.41	7.69	6.06	5.49	2.5

ties; treatment dummies (Female or male), interacting with failing or succeeding in the previous attempt ('L.fail' and 'L.gain', respectively), and total gains accumulated up to current period. We also include dummies for incentives used in each session (not reported in the table, and mostly not significant).

Table 5: **Determinants of choice**

Variable	**OLS**	**RE**	**Fem.Adu**	**Fem.Chi**	**Male.Adu**	**Male.Chi**
	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)	(Std. Err.)
First period	0.072^{*}	0.076^{*}	0.273^{**}	0.008	0.099^{*}	-0.045
	(0.033)	(0.032)	(0.086)	(0.052)	(0.040)	(0.032)
Risk level	-22.606^{**}	-22.497^{**}	-19.776^{**}	-17.618^{**}	-39.788^{**}	-36.787^{**}
	(2.228)	(0.820)	(1.903)	(1.068)	(2.186)	(1.350)
Fem#L.fail	0.253^{*}	$0.223^{\dagger}$	-0.006	0.290		
	(0.126)	(0.131)	(0.196)	(0.186)		
Male#L.gain	0.093	0.122				
	(0.127)	(0.145)				
Male#L.fail	$0.272^{\dagger}$	0.202			-0.039	0.041
	(0.153)	(0.156)			(0.140)	(0.143)
Lag score	0.039^{**}	0.039^{**}	$0.046^{\dagger}$	0.040	0.021^{*}	0.022
	(0.013)	(0.011)	(0.026)	(0.026)	(0.010)	(0.017)
Intercept	6.131^{**}	6.127^{**}	5.307^{**}	5.707^{**}	7.854^{**}	8.029^{**}
	(0.303)	(0.191)	(0.460)	(0.265)	(0.327)	(0.218)
	$N = 356$	$N = 356$	$N = 64$	$N = 108$	$N = 84$	$N = 100$

Controls: sessions. OLS: individual-clustered SE.

Significance levels: $\dagger$: 10% $\quad *$: 5% $\quad **$: 1%

The first two columns report results based on overall data; these are qualitatively very similar. More challenging choice in the first period implies higher overall proclivity to take risky decisions. Subsequent columns show the same tendency is also true for adults but not for children. Riskiness (difficulty of the task) is also highly and negatively significant, which is expected. Controlling for other factors, females tend to increase their bids following failure to a larger extent than following success. Males, by contrast, are not responsive to successes and failures. This suggest that males are generally more 'stubborn' follow their strategies regardless of the signals, whereas females tend to be more responsive, trying to maintain the balance of earnings. This somewhat unexpected result seems to be driven by the 'Risk level': once this variable is omitted, significance of that treatment disappears. Finally, lagged accumulated earnings lead to more challenging decisions for adults but not for children. Altogether, this evidence implies that

Result 3 *Adults react to incentives and are more persistent in their choices than children. Females tend to be more adaptive in their strategies than males.*

4.4 Comparisons with other tests

Another legitimate question is how our test measure fares against other classical measures of risk attitudes. Table 6 reports Pearson correlation coefficients of the four measures for a subset of our (adult) subjects who answered all questions ($N = 33$). The first two are: 1) canonical Holt-Laury type lotteries, with higher number corresponding to lower switching in range, i.e. higher risk aversion; 2) self-reported measures, i.e. answers to question "How much do you like risk, at a scale from 1 to 10", both measured at nominal scales from 1 to 10. Last two are measures based on our experimental technique: 3) arithmetic mean sector number, out of 5 sectors chosen by the subject, and 4) First choice made by the subject, as a first and most intuitive decision made before any feedback. Scales of questions are somewhat different, but since we are interested in correlations only, Pearson correlation test is valid qualitatively; estimates based on Spearman and Kendall correlations gave qualitatively similar results.

Table 6: **Correlations between risk preference measures (p-values in parentheses)**

measures	Holt-Laury	Self-reported	Our measure
1) Holt-Laury			
2) Self-reported	-0.199		
	(0.266)		
3) Our measure	-0.072	0.252	
	(0.690)	(0.157)	
4) Our measure (1)	-0.032	0.114	0.426
	(0.858)	(0.537)	(0.013)

As Table 6 reveals, measures are generally poorly correlated in our subsample. This is not surprising: all measures are procedure- and context-dependent, and such inconsistency happens rather often. Our measure performs neither better nor worse in this respect, except for the fact that the overall measure of riskiness of choices (mean sector chosen over 5 attempts) is significantly, albeit not very strongly (just 46%) correlated with the choice at first attempt, which maybe deemed 'pure' in the sense of being feedback-free. It follows that our measure of choice riskiness is in principle intrinsically consistent.

Result 4 *Prior risk measures reveal poor correlation with our (Bayesian) risk measures, while Bayesian risk measures are consistent within trials.*

Conclusion about preferences robustness, however, is only to a limited extent true of within-subject trials. In a subsample of 39 individuals, our measure has been applied twice to the same cohort of students playing for course grade points ($N = 39$). These tests have shown some consistency, but not at a very high level (Cronbach alpha = 0.444).

Taken together, these considerations seem to imply two related conclusions. First, preferences towards risky options are again shown to depend on the context of the task (form of question, and/or flows of successes and failures), plus perhaps subjective factors (mood of the subject). Second, and more importantly, our empirical measures are internally consistent, but they measure something *different* from the conventional ones: our measures deal with Bayesian risk preferences, the conventional ones — with prior risks. However, our measures do not yet represent attitudes to risks per se — rather, these are raw revealed preferences in risky situations. How can we proceed to proper measures of attitudes towards Bayesian risks?

5 Bayesian model

In previous section we have considered the overall interpretation of our experimental measure of observed choices under risk. However, as argued above, in our dynamic settings risk preferences (in the narrow sense of risk aversion, measured by a single number) are intertwined with aspirations, or beliefs in own abilities to tackle the problem in question. We now proceed with disentangling these two by means of a simple model.

5.1 Model specification

To proceed, we assume that (typical) individual is rational in the sense of von Neumann-Morgenstern, i.e. tries to maximize his/her expected gain, given her preferences for risk and believed abilities (aspirations) to cope with the experimental task. We further assume that: 1) measures of risk preferences and aspiration levels are statistically independent; 2) risk aversion is an exogenously predetermined individual parameter which the subject gradually learns, while 3) aspirations are rationally formed as posterior beliefs about own abilities in a closed-loop feedback mechanism. And of course, we have to assume that all these characteristics are identifiable from experimental data.

These assumptions are neither fungible not innocuous. In almost all economic models, risk aversion is treated as immanent individual characteristic, which is known to the subject who makes her decisions conditional on it. Almost all neoclassical decision theories generically assume that individuals maximise the utility function $U(x, p|r)$, where x and p are vectors of outcomes and their respective probabilities, and r a (scalar or vector) characteristic of risk preferences (risk aversion parameter). Further to that, almost all theories of choice under risk are silent about the origins of risk preferences. One of the most plausible explanation for them seems to be evolutionary: decision-makers have learned their r's in the course of lifetime repeated interactions with risky prospects/lotteries. This specification would match with our taxonomy of risks as *prior* and *Bayesian*: long term prior attitudes are stationary outcomes of evolutionary process of learning how to deal with dynamic risks. This learning, however, must take place in immediate interaction with the risky environment, so the learning subject has to reveal some attitudes towards it, i.e. her aspirations. Hence, the general specification of our utility function defined above is $U(x, p|r, \theta)$ which we have defined above.

Individual aspiration level is a psychological characteristic, which in our environment needs to be discovered and updated in light of new information. We assume that individual belief in own abilities θ is never known a priori, but is described by beta distribution with hyperparameters a and b. This distribution is convenient for several reasons. First, it is limited to unit segment whose lower and upper end corresponds to low and high perceived abilities, respectively. This distribution is flexible: various combinations of hyperparameters give rise to different shapes to the distribution of θ. Finally, outcomes of subsequent interactions with the environment result in either success or failure — a binomial distribution, for which beta prior constitutes a conjugate family: if prior is beta and the likelihood is binomial, the posterior is also beta. Inasmuch as the subject makes repeated decisions under binomial feedback, his or her posterior about own abilities is updated, in the limit — up to the stationary point, wherein the subject sticks at the long-term expectation, which coincides with and true value of her abilities. Bayesian preferences for risk are superimposed on these perceived abilities, and are responsible for deviations from that posterior level. In other words, the difference between estimated posterior abilities and observed decisions constitute a proper measure of Bayesian risk preferences.

Of course, our specification of abilities is only a particular case, adopted here largely for convenience and tractabilities. Priors about own beliefs may differ across individuals — for instance, some people may have Gamma priors and Poisson likelihoods, or beliefs of exponential family etc. Updating of beliefs also need not necessarily be literally consistent with Bayes rule: abundant experimental evidence suggests that many people are poor intuitive statisticians. However, the principles of rationality and Bayesian learning suggest that learning dynamics should be simple, and driven by incentives. Hence, our estimation approach can be viewed as both the benchmark case and prototype story for general learning of one's preferences for dynamic risk.

In terms of our experiment, a typical individual makes her first attempt being guided by a combination of both factors: prior risk preferences and prior aspirations, which cannot be disentangled at first. Let $x = \{1, 2 \ldots 8\}$ be the set of possible choices, constant across individuals and attempts. We use x_k, $k = 1, 2 \ldots 8$ to denote elements of this set. Let y_t be the choice of individual in period t (one of the x_k's), $u(\cdot)$ — her utility function over outcomes (for simplicity, proportional to gains), and s_{kt} — the subjective probability that she will succeed at choice k in attempt t (in trial 1, this includes both aspiration and risk preferences). Assumption of rationality implies the first choice of one of the x_k's shall maximize the subjective utility over all 8 possible decisions, given the prior belief (aspiration) about her abilities:

$$y_1 = \arg\max_{x_{k1}} u(x_{k1}) s_{k1} \tag{1}$$

With these subjective belief is conditional on prior abilities θ which follows the beta distribution with prior density

$$s_{k1} = \theta^a (1 - \theta)^b \tag{2}$$

that is, $\theta \propto B(a, b)$, where parameters a and b can be estimated by maximum likelihood given the first choices. Evidence about outcome of the first trial $\delta = \{1, 0\}$ defines posterior density θ_1 as

$$s_{k2}(\theta_1|\delta) = \theta^\delta(1-\theta)^{1-\delta}\theta^{a-1}(1-\theta)^{b-1} = \theta^{\delta+a-1}(1-\theta)^{1-\delta+b-1} = B(\theta|a+\delta, b+1-\delta) \tag{3}$$

which makes use of the conjugate property of the beta distribution: if prior is beta and evidence comes from the binomial distribution (corresponding to success and failure at previous attempt), then the posterior is also beta, so that it can be used as dynamic measure of abilities. Repeating this recursively for each trial, we obtain optimal choice $\hat{x}_{kt}$ as inverse to beta distribution. We interpret the mean of this posterior beta at the final, fifth period as an estimate of individual abilities, measured separately by treatment categories (females-males, adults-children). Risk preferences parameters by the same categories are then calculated as the differences between factual decisions y_t and fitted abilities $\hat{x}_{kt}$ at the final, fifth trial, i.e.

$$r = y_5 - \hat{x}_{k5}. \tag{4}$$

5.2 Estimation results

In general, our model (1) admits many different specifications, and subsequent estimations are conditional upon them. Figure 9 shows several possible utilities' profiles under alternative specifications of probabilities and utilities (from top to bottom): probabilities proportional to areas of the sectors as specified in Table 4 with linear utilities, CRRA utilities with risk aversion 0.15 and 0.85, and uniform (equiprobable) chances of success in each sector with CRRA of 0.5. As the figure shows, utility-maximizing choice of the sector generally depends on these specifications: the first two stipulate choice of sector 3, the third one — of sector 1, the last one — of sector 7.

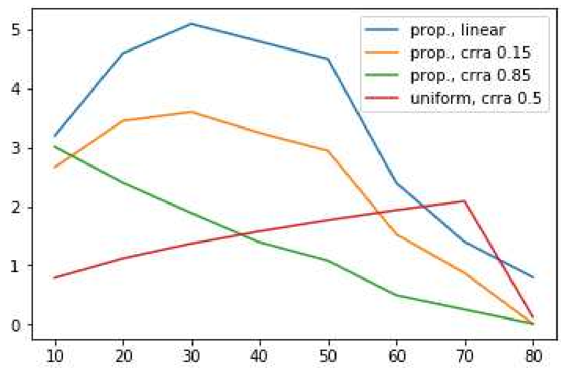

Figure 9: Utilities' profiles under different model specifications

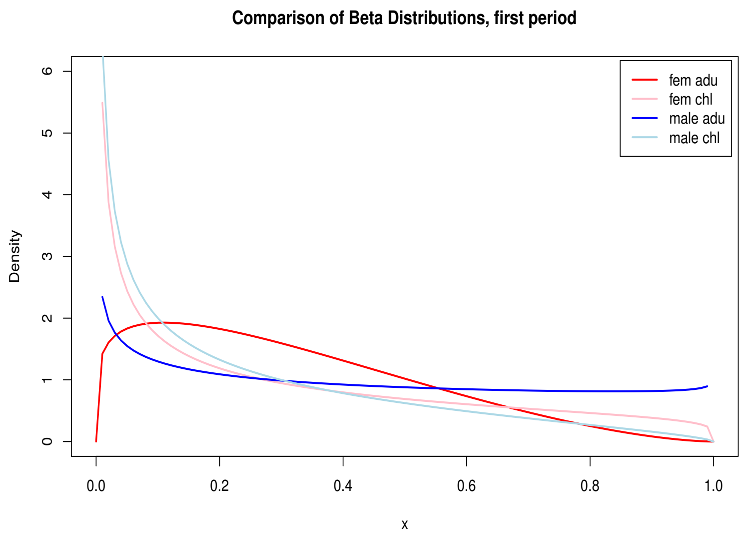

Figure 10: Prior distributions of abilities by categories

Because the task is novel to all subjects, we assume a uniform prior, and estimate the prior beta parameters for all four treatment types whose decisions are assumed to maximize the product of uniform priors and normalized number of points to be earned in each category. Fits of prior beta parameters based on first-period choices has been made using `betafit` package for Stata 14. Initial estimates are presented in Table 7.

Table 7: Prior beta parameters

		Fem Adu		Fem Child		Male Adu		Male Child	
Estimates	Value	Coef.	(St.Err.)	Coef.	(St.Err.)	Coef.	(St.Err.)	Coef	(St.Err.)
Priors	a	1.204	(0.384)	0.501	(0.115)	0.748	(0.206)	0.519	(0.123)
	b	2.638	(0.936)	0.180	(0.332)	0.949	(0.276)	1.677	(0.513)
Posteriors	a	3.026	(1.515)	2.237	(1.454)	2.770	(1.403)	1.960	(1.601)
	b	3.901	(0.941)	4.433	(0.823)	2.210	(0.930)	2.930	(1.150)
	mean	1.477	(2.230)	2.185	(2.540)	2.730	(3.233)	2.388	(3.602)
Bayesian Risk Aversion		1.474	(2.231)	1.933	(1.844)	1.851	(3.071)	2.576	(4.286)
		$N = 16$		$N = 27$		$N = 21$		$N = 25$	

All estimates are highly statistically significant, allowing us to proceed with the estimations of posterior abilities and risk preferences. Plot of the prior aspirations corresponding to these estimates is presented on Figure 10: as can be seen, it generally implies rather low level of confidence, especially for children.

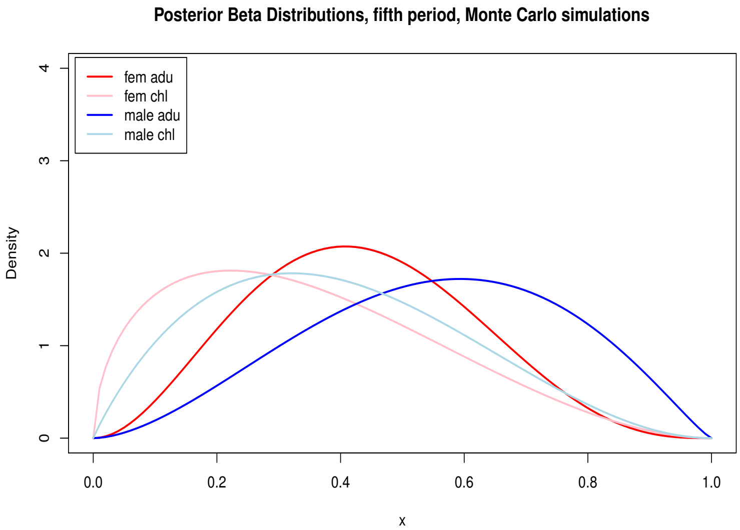

Figure 11: Posterior distributions of abilities by categories

Lower section of Table 7 presents posterior estimates after period 5, and Figure 11 plots the beta distributions of the corresponding estimated abilities. As can be seen from that picture, abilities are updated in comparison to priors: all subjects become more confident, with males more confident than females (of all ages). Accompanying comparison of means of final distribution show that observable behaviour (chosen difficulty levels, as presented in section 4) is attributable to *both* aspirations and risk preferences, in about equal proportions. In particular, resulting estimates of Bayesian risk aversion (calculated as in (4), with higher numbers corresponding to more risky choices) imply that Bayesian risk tolerance is highest among boys, while that measure does not significantly differ across gender for adults.

These results, however, are of limited power, for a number of reasons. First of all, due to restrictions of our data to motivated decisions, all sampled are small, and standard errors of both abilities and Bayesian risk attitudes are large: none of the parameter estimates are generally robust. To address that issue using our data, we have complemented the above analysis using Monte Carlo simulations from the original parameter values estimated in the upper part of Table 7, assuming normal distribution with these values as means and standard deviations of 1/2 of these (in case the draws yielded negative numbers, these values are taken to be 0.01). Resulting distribution of the bayesian risk parameters are shown on Figure 12.

Estimated risk aversion parameters and their standard errors are more robust, always significant, and reveal some interesting patterns. Mean risk preferences do not differ significantly across genders for children and adult, but do differ for children ($t = 4.85, p < 0.000$). Significant are also differences between risk attitudes of males

Table 8: **Results of Monte-Carlo simulations**

Age	Adults				Children			
Gender	Male		Female		Male		Female	
stats	Mean	(Std.Dev.)	mean	(Std.Dev.)	mean	(Std.Dev.)	mean	(Std.Dev.)
mean	2.180	(3.118)	2.244	(2.940)	3.214	(3.666)	2.303	(3.030)
median	2.222	(3.088)	2.264	(2.945)	3.054	(3.881)	2.316	(3.018)
st.dev	0.728	(0.480)	0.679	(0.415)	0.859	(0.772)	0.400	(0.201)

($t = 6.18, p < 0.000$), but not of females. An interpretation of these results would be that most gender differences in risk preferences in our dynamic (Bayesian) context is due to aspirations: males are more self-confident and willing to assume more challenging tasks, while Bayesian risk preferences do not differ across genders. This is not true of children though: boys are both systematically more ambitious and more willing to take risks than girls.

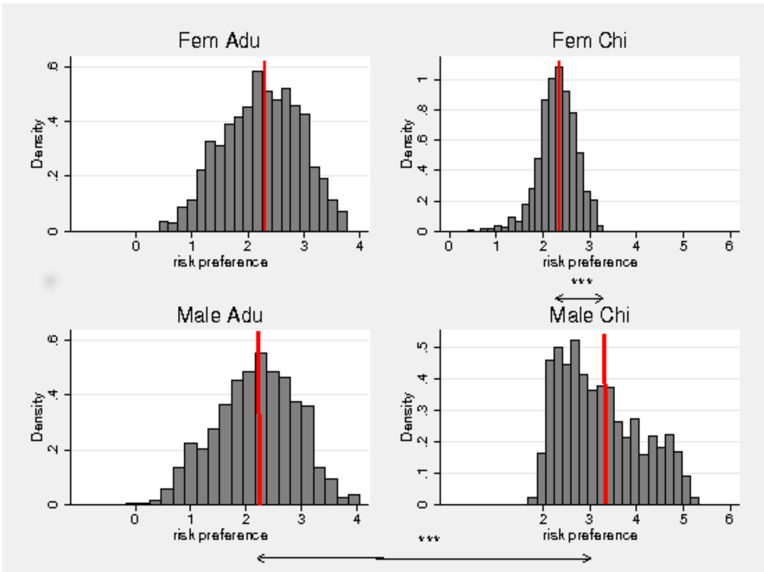

Figure 12: Bayesian risk aversion from Monte-Carlo simulations

Recalling our interpretation of prior risk preferences that are measured in all existing tests as limiting case of dynamic risk preferences, it would also imply that common measures of risk preferences by conventional methods may be mixing the same factors in analogous proportions. However, at this stage we would be cautious to jump to such conclusions. First, we have no theory or evidence to prove the conjecture that prior risk attitudes follow from dynamic ones. Second, estimates of aspirations and risk preferences do depend on Beta priors: their differences result in different conclusions, even in Monte-Carlo settings. Finally, our data is rather restrictive for a number of reasons that we discuss in the next section.

6 Limitations and conclusion

We believe the above analysis opens a new perspective in analysis of preferences under risk, as well as related issues of aspirations, beliefs and subjective confidence in own abilities, as well as gender and age differences in these characteristics. These issues are important in many aspects of modern life, yet so far they have received either unduly little, or none at all attention in the literature. The results provided and discussed appear to be insightful in many respects, the most important of which are 1) separation of aspirations/ambitions from risk preferences per se, and 2) differences among adults and children in terms of these characteristics underlying their observable choices. However, our present analysis is subject to several limitations and critiques, some of which we view as substantial.

First, the data set we have used is heterogeneous. Subjects (speaking first of all of adults) represent different cohorts, who have convened in different environments and different incentives conditions. This heterogeneity has been primarily motivated by the need to apply the same incentives to all cohorts of participants, including small children, who cannot be paid real money. This property is valuable, and bears of the main advantage of our novel measurement technique, namely its suitability for the subjects of all ages. However, for the purposes of our analysis we have limited attention to the most typical and incentivized subsample, at a cost of sample size reduction. Normally, we want to have a larger database of homogeneous subjects (at the very least, adults) who have been making decisions with proper monetary incentives. This should increase reliability of the data in terms of stimuli, as well as of the number of observations, mitigating the need to use Monte-Carlo inferences.

Further problem is short series of decisions. Again in order not to overload small children, we used the same length of 5 trials, which is likely to be insufficient to learn one's abilities, and hence leads to not very robust estimates of risk aversion. We have estimated the abilities' parameters after various periods (trials, and the series of consecutive posteriors appear to converge — but again, short series preclude any quantitative validation of this observation. We would expect the series of 15 to 20 trials sufficient to establish convergence, and ground risk measures on the resulting estimated values of abilities θ.

Next to that, we may want to manipulate incentives. After achievement of convergence, it seems natural to see if risk preferences are really related to monetary incentives, or are pure preferences per se. One way to test that might be to let the subject play the same game after convergence of strategies (estimated from previous experiences) for several more periods, but without any reward, and see if their strategies change.

Most important reservation, however, is quality of control. In any individual task using playfield from Figure 1, it is virtually impossible to ensure identity of conditions: subjects inevitably move, raise their hands and bend their heads to different extent, etc.

Further, although every care has been taken to motivate subjects to decide seriously, we cannot exclude possible cheating, especially in large rooms. Another, related problem are subjects with different motor abilities: despite the prior announcement, we cannot exclude and control for these differences, while we still value the idea of using bodily motions. To address all these concerns, we believe it will be most important to use homogeneous computerized motion task, like a dot rolling over the circle which has to be manually stopped at a particular point or sector; or several divergent particles, which offers an additional option to study the complexity of decisions. Tasks of that kind could be complemented with risk measures in other contexts, such as counting problems (multiplication of easy 2-digit, or complicated, 3-4 digit tasks with different rewards and success probabilities) or distinguishing colors of different metric distances at RGB scales. The former is typically believed to be more suitable for males, the latter — for females. Besides gender balance, leading to estimations of their respective aspirations and beliefs in own abilities, these contrasts allow us to test a novel hypothesis that notwithstanding the variety of decision problems, patterns of risk preferences (in the narrow sense of the word, separated from aspirations) shall remain the same for a given individual.

Finally, we want to consider other learning models, departing from the Beta–Binomial posteriors in several directions. A natural alternative to it is 1) the Gamma–Poisson conjugate family. More generally, we need to consider imperfect learning, starting from 2) adaptive rule: for $t \geq 1$,

$$\theta_t = \lambda\theta_{t-1} + (1-\lambda)\hat{\theta}_t \tag{5}$$

where $\hat{\theta}_t \in 0, 1$ is fitted ability of the present period, $\theta t - 1$ is previous period's believed ability, and λ is adaptation parameter: θ_t adjusts every period with parameter λ. Alternatively, it can be 3) Markov model when signal can be interpreted as correct or incorrect (erroneous):

$$\theta_t = \mu\theta_{t-1} + (1-\mu)\hat{\theta}_t \tag{6}$$

where μ is Markov probability of 'true' and 'false' signal: with probability μ the believed ability θ_t adjusts, with complementary probability it stays the same. This model can be viewed as adaptive: the person learns with probability $1-\mu$, and holds the same beliefs about his/her abilities with complementary probability. Or, we can use 5) learning with random noise

$$\theta_t = \epsilon\tilde{\theta} + (1-\epsilon)\hat{\theta}_t \tag{7}$$

where with (presumably large) probability $1-\epsilon$ the person adopts correct beliefs about his/her abilities, and with complementary probability adopts any belief $\tilde{\theta} \sim \mathcal{N}(\theta_t, \sigma^2)$. Finally, we can consider various instances of 6) reinforcement learning rules.

Comments are welcomed!

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