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Are risk-seekers more optimistic? Non-parametric approach☆

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ABSTRACT

Class and field surveys revealed that personal inclination to take structured lottery-risk significantly correlates with optimism in financial forecasting. Trait optimism reflects in return predictions for successful and problematic stocks, in likelihood assessments of specific events, and even when respondents recollect past realizations. Gain-domain risk preference shows the strongest predictive power for forecast positivity, even when macro expectations, win-chance optimism and personal attributes are controlled. The correlations are strongest when optimism scores are derived from multiple prediction tasks, but quickly dissolve when subjects receive usable anchors. The findings are discussed in light of optimism scope and recent research on ambiguity aversion.

1. Introduction

The distinction between conditions of risk, where the probabilities of outcomes are objectively known, and cases of uncertainty (Knight, 1921) or ambiguity (Ellsberg, 1961), where chances are unclear, still draws wide interest in economic research. Recent studies, in particular, suggest that receptiveness to risk correlates with positive ambiguity attitude (e.g., Bossaerts et al., 2007; Lauriola et al., 2007; Chakravarty and Roy, 2009; Charness and Gneezy, 2010), and trait optimism was proposed as possible explanation (Trautmann and van de Kuilen, 2013).[1] With this motivation, the current study investigates the link between risk appetite and forecast positivity, testing if risk-tolerant individuals hold more optimistic beliefs regarding future economic uncertainties.

We take a non-parametric approach to the examination, disconnecting from formal theories of choice when characterizing the tendency to take risk, and mixing over diverse domains, methods and frames while assessing relative forecast positivity.

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[1] Bossaerts et al. (2007) show that diversification patterns correlate under risk and ambiguity, while Charness and Gneezy (2010) demonstrate that subjects that select into ambiguous markets allocate higher proportion to risky investment. Chakravarty and Roy (2009) use multiple price lists, finding positive significant correlation in gain-domain. Lauriola et al. (2007) prove that such correlations emerge even when the conditions are run in separate semesters.

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The paper may thus classify as a correlational study, where on one hand we measure risk-preference in structured lottery-choice assignments and on the other we approximate personal optimism with respect to economic or financial uncertainties. Since positive correlations may arise or withdraw from mediating effects such as gender, wealth, or education, we control for these and other confounds, also testing if risk-preference appears to boost optimism beyond general macro expectations.

Additional motivation arrives from the interdisciplinary interest in optimism. Psychology studies treat optimism as a rather stable personality trait, using customary questionnaires such as LOT-R (Scheier et al., 1994) to measure life-course expectations. The choice literature definition (see, Hey, 1984 for earlier discussion; Dillenberger et al., 2012 for recent example) disconnects from the personal perspective, defining optimism in terms of subjective beliefs over events that are far beyond the control of the decision maker. Empirical studies utilize other, ad hoc, definitions; e.g., Puri and Robinson (2007) use the difference between expected life spans and actuarial estimates, showing that optimistic individuals work longer, save more, and exhibit stock-picking behavior. The expanding literature demonstrates that optimists use short-term debt extensively (Landier and Thesmar, 2009); adopt tougher positions in bargaining (Dickinson, 2006); show increased likelihood of mortgage arrears (Dawson and Henley, 2012) and discount the future less heavily (Shavit et al., 2013). From the optimism-definition standpoint, our study explores the scope of personal positivity, testing if optimism jointly reflects in remote domains such as experimental lottery-choice and case-specific economic forecasting.

We have run two incentivized surveys that did not mention the words optimism or pessimism and were introduced as studies of macroeconomic and stock-market expectations. Psychometric tests of optimism such as LOT-R were avoided to decrease the risk that participants recognize the main research question.[2] The first shorter questionnaire ($N = 75$) was distributed in large dining centers to attract participants of diverse background. The second comprehensive survey ($N = 73$) was run in MBA classes. Both studies revealed positive significant correlations, around 0.45, between relative forecast-optimism and individual inclination to take experimental lottery-risk. The proportion of risky choices in gain-domain problems emerges as the most significant predictor of forecast-optimism in both studies, although the risk-preference elicitation tasks were very different. The correlation is strongest at the aggregate, when optimism is evaluated with respect to multiple prediction targets, but it quickly dissolves when a numeric anchor is provided with the forecasting assignment. More generally, the predictive power of personal risk-preference for forecast-positivity appears to significantly strengthen with underlying target uncertainty. The correlation is highly significant when respondents predict the few-years performance of volatile stocks, but it almost dissolves in predictions of monthly returns on heavy stock indices. Our results, with this respect, support the cognitive or informational account of dispositional optimism, beyond the motivational explanation (Coelho, 2010). Optimistic types tend to retrieve or access more positive evidence when contemplating forecasts. As the dispersion of signals increases with underlying uncertainty, the distance between the forecasts of optimistic risk-seekers and pessimistic risk-averters rises in parallel.

Optimism studies sometimes distinguish between "trait optimism" representing the basic dispositional inclination and "state optimism" which may be affected by temporary conditions (e.g., Burke et al., 2000). Generally optimistic individuals come out relatively pessimistic in particular contexts where state-related effects override their fundamental positivity (Kluemper et al., 2009). Indeed, Wenglert and Rosén (2000) find that life-events optimism shows only moderate correlation with optimism regarding worldwide events. If economic predictions are strongly influenced by personal states while risk attitudes are relatively immune to transitory effects (Harrison et al., 2005; Sahm, 2007; Zyphur et al., 2009), then the forecasts of risk-seekers may not appear more optimistic. The 0.45 correlations between gain-domain risk chasing and forecast-optimism are therefore rather surprising. While the correlations could follow from universal tendency of optimistic individuals for positive expectations (in choice and in prediction), a control for "win-chance optimism" could not explain the results. Respondents that overestimated their success rates in repeated coin-flips took more risk in the lottery-choice assignments, but the hypothesis that "win-chance optimism" mediates the correlation between forecast-optimism and risk-preference was rejected for both surveys.[3]

Interestingly, our results for loss-domain risk-preferences are negative. When the gain-domain measures are replaced by parallel loss-domain risk-tolerance scores, the correlations between risk-preference and forecast-positivity strongly deteriorate. As part of the psychology literature treats optimism and pessimism as distinct constructs (Chang et al., 1997), we also test if gain-side risk-preference is a stronger predictor of positive-domain optimism, while loss-side risk-preference obtains stronger correlations with negative-domain forecasts (e.g., predictions of the loss on problematic stocks). The refined hypothesis, however, is clearly rejected for both surveys. The weaker results for loss-domain choices are attributed to the lower levels of consistency and higher noise that generally characterize loss-related decisions (e.g., Abdellaoui et al., 2013).

Together with preceding research, the results of our surveys propose that the positive correlation between risk and ambiguity attitudes may have two distinct roots. Abdellaoui et al. (2011) show that risk-receptive individuals exhibit relatively optimistic choice patterns under uncertainty, when personal beliefs are controlled. The results of the current paper additionally propose that the risk-tolerant generally hold more optimistic views in cases of uncertainty. In uncertain investment

[2] We suspected that if the survey is perceived as an optimism study, self-classification and experimenter demand effects might bias results. Following a referee comment, we distributed the LOT-R to survey II participants about 2 years later. 50% responded. LOT-R positively correlated with risk-preference, but did not correlate with forecast optimism. The details are provided in Section 4.4.

[3] As risk-preferences are rather stable, while forecast-optimism may vary with selected uncertainties and personal states, we treat optimism as the dependent variable throughout the analysis.

context, for example, our results imply that the relatively risk-seeking would hold more positive expectations regarding the return on investment, while the Abdellaoui et al. (2011) results propose that the relatively risk-seekers would choose more risky allocations even when subjective beliefs are controlled. At the applicative level, the two-fold correlations suggest that risk-preference tests may prove useful as psychometric instruments for measuring susceptibility to unrealistic optimism (Weinstein, 1980). Lottery-choice questionnaires could be easily implemented to forewarn money managers that are prone to hasty speculations or characterize entrepreneurs with large chances for unsuccessful ventures.

The paper proceeds as follows: Section 2 presents our three formal hypotheses. Sections 3 and 4 discuss the field and class surveys while Section 5 concludes.

2. Hypotheses

While the evidence regarding the correlation between risk and ambiguity attitudes is mostly positive, several studies find close to zero and even negative association (Trautmann and van de Kuilen, 2013). The distinction between trait and state optimism (Burke et al., 2000) casts more doubt on whether risk-seeking individuals would hold more optimistic views under uncertainty. Moreover, even if risk-tolerance correlates with forecast-optimism, the correlation may arise from basic tendency of the optimists to overweight the positive prospects in lottery choice and in economic forecasting. While these doubts strengthen our motivation, we choose to formulate the main hypothesis in positive terms:

H1 – Risk-preference correlates with forecast optimism. Decision-makers that take more risk in structured lottery-choice assignments, deliver relatively optimistic predictions under uncertainty. The correlation sustains when personal tendency to overweight exogenous win-chance probabilities is controlled.[4]

The secondary hypotheses H2–H3 below deal with the informational roots of dispositional optimism. The literature on "cognitive optimism" argues that the information processing of optimists is naturally biased toward positive evidence (Metcalfe, 1998). Experimental studies confirm that optimists show higher subconscious attendance to positive data, while exhibiting higher resistance to negative stimuli (e.g., Segerstrom, 2001; Isaacowitz, 2005). Several finance studies (e.g., Diether et al., 2002; Jiang et al., 2005) accordingly claim that disparities between optimistic and pessimistic analysts widens with uncertainty, as the space of plausible signals expands and opens room for differences in opinion.[5] To manipulate target uncertainty, we provide an applicable anchor in some of the prediction assignments, while forbidding Web and peer consultation (to prohibit on-the-spot anchoring) in general. Assuming that the anchors decrease the dispersion of possible assessments, we hypothesize that the link between risk preference and optimism would reduce:

H2 – informational roots. The correlation between risk-preference and forecast-optimism diminishes when respondents receive a relevant anchor with the prediction assignment.

An obvious shortcoming of the measurement of optimism by case specific predictions is that responses may be affected by random experiences (such as the newspaper article that the respondent recently sampled), and can be tainted by the position of the participant with respect to the target (e.g., optimism may reflect in negative predictions if the investor recently sold the stock). These case specific biases, however, should cancel out when optimism scores are derived from multiple, distinct prediction targets. H3 accordingly stipulates that the correlation between risk-preference and forecast-optimism should strengthen on the aggregate:

H3 – aggregation. The correlation between risk-preference and forecast-optimism strengthens when optimism scores are derived from several anchor-free predictions.

3. The field survey

3.1. Method and participants

The questionnaire was distributed at the dining areas of shopping centers and few major employers. The interviewer randomly approached possible respondents, proposing participation in a short prize-paying economic prediction survey. To avoid unfit participants, we employed a "3 listed stocks" screening test. Candidates that could not list three of the stocks traded at the Tel-Aviv exchange were excused. The interviewer supervised participants closely, prohibiting peer or media consultation. The left panel of Table 1 provides descriptive statistics for the final sample ($N = 75$).[6] The participants that

[4] The "APPARENT risk tolerance" of expectations-optimistic individuals could represent a more basic tendency to under evaluate risk, in choice and in prediction. The hypothesis claims that the correlation between risk-preference and forecast-optimism sustains beyond such distortion. We thank a referee for illuminating the distinction.

[5] The literature proceeds claiming that when short-sale restrictions or other factors prohibit arbitrage, the high-uncertainty stocks would be temporarily traded in exaggerated prices because of the unbalanced demand of optimistic traders.

[6] We collected 82 questionnaires but removed seven for inconsistent choices. The translated script is provided in Web supplement A. The filtering is explained in supplement B. We used two counterbalanced versions (prediction-choice vs. choice-prediction). The main results show for both. The class (field) surveys were run in June (August) 2012 where the US$ was traded for 3.80–3.86 NIS.

Table 1
Descriptive statistics.

	Field survey ($N=75$)			Class survey ($N=73$)		
	Mean (STD)	P10	P90	Mean (STD)	P10	P90
Age	33 (9.0)	25	44	31 (4.8)	27	37
Years of education	15.8 (2.0)	13	18	16.9 (1.2)	16	18
Male	69.7%	–	–	60.3%	–	–
Married	56.6%			46.6%		
MBA (%)	28.0%	–	–	100.0%	–	–
Financial industry (%)	17.3%	–	–	48.7%	–	–
Market familiarity	3.8 (2.3)	1	7	–	–	–
Economic status	5.8 (2.0)	3	8	6.4 (1.4)	5	8
Health condition	8.4 (1.7)	6	10	8.6 (1.5)	7	10
Recent mood	7.3 (1.8)	5	9	7.4 (1.5)	5	9
Career satisfaction	7.6 (1.8)	5	10	7.2 (1.7)	5	9

STD denotes the standard deviation. P10 (P90) are the 10% (90%) deciles. MBA is an indicator for holding or pursuing the degree. Financial industry indicates investment-industry job. Market familiarity, economic status, health condition, mood and career satisfaction were reported in 1–10 scale with 1 denoting the weakest position. The rankings were collected at the last page of each survey. Familiarity was not elicited in the class survey.

Table 2
Lottery choice tasks–field survey.

Problem	The risky lottery	The safe lottery	Δ(expected payoff)	%(safe choice)
GAINS1	1000 or 200	700 or 600	−50	97.3%
GAINS2	900 or 100	550 or 450	0	94.7%
GAINS3	900 or 0	400 or 350	+75	88.0%
GAINS4	1000 or 250	550 or 400	+150	57.3%
GAINS5	1000 or 100	300 or 200	+300	36.0%
LOSSES1	−900 or −100	−600 or −500	+50	26.7%
LOSSES2	−1000 or −200	−650 or −550	0	45.3%
LOSSES3	−1000 or −100	−500 or −450	−75	66.7%
LOSSES4	−1000 or −250	−550 or −400	−150	86.7%
LOSSES5	−900 or 0	−200 or −100	−300	94.7%

selected into the survey and passed the 3-stocks screening are highly educated (mean formal education years 15.8, implying some level of graduate studies) with large proportion of MBAs and financial-industry employees. The pool however appears quite diverse in terms of age, economic well-being, stock-market familiarity and proclaimed mood.

The words "optimism" and "risk" were avoided throughout the questionnaire (except for the GALLUP problem discussed below) and the research was introduced as "survey on prediction and economic decision". About 1/3 of the participants were randomly selected to receive an instant payout of 40 NIS (roughly 10 US$). The instructions, in addition, explained that two respondents would be randomly drawn to receive larger prizes that could reach 200 NIS or more. The bonus of the first winner would be derived by drawing one of selected lotteries, while the prize of the second winner would increase with the accuracy of a numeric prediction. The bonus formulas and date of payment were not announced in advance. The questionnaire emphasized that the bonuses were designed to promote careful deliberation of each choice and prediction, and the exact formulas would be emailed when the bonuses are announced.[7]

3.2. Risk attitudes

Table 2 displays the 10 binary choice problems that were used to characterize personal risk-attitudes. Payoffs were only positive in GAINS1–GAINS5. Respondents were asked to assume that personal or business-related circumstances have generated a gain whose final amount has not been determined yet, and choose one of two possible distributions. In GAINS1, for example, the choice is between a risky lottery paying 1000 or 200 with 50% chances and a safer lottery paying 700 or 600 with equal probabilities. We only used 50% probabilities throughout the assignments to simplify the tasks and ease the control for subjective win-chance weighting (see discussion of $\Pi(50\%)$ below).[8] The five gain-side problems, in general, asked participants to choose between a risky alternative paying X or Y and a safer option paying V or W, where $X>V>W>Y>0$. The five problems were constructed so that the incentives to take risk, in terms of the difference in expected payoffs $0.5*(X+Y-V-W)$, successively increase with the running-number of the problem. The risky lottery paid 50 NIS

[7] We used imprecise incentives (in both surveys) to circumvent the problems that arise with incentivization of loss-domain choices and 3–5 years predictions. The experimenter was instructed to clarify (if questions arise) that the bonus would decrease in the amount of realized loss if the payout lottery is loss-domain. The class-survey bonuses were actually announced in May 2013. The lottery winner received 200 NIS for choosing the low risk option in GAINS5. The prediction bonus, 105 NIS, was determined by the formula 150–30*(predicted – realized unemployment in March 2013).

[8] Preceding studies (cf. Henrich and Richard, 2002) suggest that subjects show stronger tendency to take risk with 50–50 gambles, but we do not believe (or aware of evidence suggesting) that the use of such lotteries affects the relative ranking of subjects in terms of personal risk-preference.

less than the safe alternative in GAINS1, where only risk-seekers that are willing to sacrifice payoff for risk could prefer the risky prospect. Expected payoffs were equal in GAINS2, where payoff maximizers could arbitrarily choose the risky or the safe option. The premium for taking risk became positive 75 in GAINS3, increased to 150 in GAINS4, reaching 300 NIS in GAINS5, where the risky alternative was twice more profitable than the safe. The five gain-side problems were presented at the same page in mixed order, with random assignment of the risky alternative as A or B.

In addition we included five loss-side choice problems (LOSSES1–LOSSES5) with only negative payoffs. The problems were presented on a separate page, asking respondents to imagine that personal or business-related circumstances brought a loss whose actual amount has not been finalized. Participants were asked to choose between a risky alternative where the loss could reach an extreme amount of X or reduce to minimal level of Y, and a safer option with intermediate loss levels V or W, where $X < V < W < Y < 0$.[9] In LOSSES1, the risky lottery was 50 NIS cheaper than the safe alternative, in terms of expected loss. If decision-makers chase risk in loss-domain (Kahneman and Tversky, 1979), then the risky option should clearly appear more attractive in this case. The risky and safe lotteries were equally attractive, in terms of expected loss, in LOSSES2. In this case, risk-neutral respondents could be indifferent. The incentives to avoid risk ($0.5 * (V + W - X - Y)$), however, became positive 75 in LOSSES3, climbing further to 150 in LOSSES4 and 300 in LOSSES5. The five problems therefore discern individual inclination to take risk when losses occur, by finding the amount of additional expected loss that the participant is willing to bear for picking riskier alternatives. Assuming that the range of premia for taking risk (in gain domain) or avoiding risk (in loss domain) is broad enough to screen our pool, we conjectured that (I) the proportion of safe choices would decrease with the running number of the problem in GAINS1–GAINS5 (II) the proportion of safe choices would increase with the index in LOSSES1–LOSSES5. The results, at the rightmost column of Table 2, clearly support both hypotheses. Kahneman and Tversky's (1979) reflection principle shows in comparison of GAINS2, where almost 95% chose the safe option to LOSSES2 where 55% preferred to take risk.[10] The proportion of risk-averse choices with gains is significantly larger than the proportion of risk-seeking choices with losses (74.6% vs. 36.0%; $p < 0.01$ by signed-rank test on $N = 75$ differences), in line with diverse preceding evidence (cf. Table 1 in Baucells and Villasís, 2010).

3.3. The prediction tasks

The shorter field survey consisted of only seven core numeric prediction tasks: six anchor-free assignments and one anchored task (this was extended to 25 problems in the class survey). The six anchor-free problems were organized in three pairs of semantically similar problems. The first problem tested for relative optimism in predicting positive outcomes, while the other similarly tested for pessimism in forecasting negative events. In selecting the specific targets for each pair we attempted to choose distant objects in terms of idiosyncratic risk, to classify individual positivity in remote applications.

The first pair of problems (P1–N1), in particular, asked participants to point predict the performance of key economic indicators in 2013–2014. P1 addressed the heaviest stock at the local exchange, asking for point estimates of its biannual return in 2013–2014. Problem N1, on the contrary, briefly referred to the lingering economic crisis in Europe, asking for estimates of the additional decrease in the EURO value in terms of US dollars over the next two years. Participants that disagreed with the basic premise of the prediction problem (positive return in P1; additional depreciation in N1) were instructed, in smaller font, to modify the text accordingly; e.g., change "decrease" to "increase" in estimating the change in EURO–US$ rate.

Predictions were preceded by stock-selection in the next pair of problems. P2 was positively framed, asking participants to choose one of the two largest commercial-banking stocks for 4-year investment, and provide their best estimate of the expected return in the respective period. N2 similarly addressed two problematic, but highly liquid, retail chain-store stocks. The respondents selected the stock that is expected to show weaker performance over the next 3 years, and estimated the loss to investors over the respective period.

The third pair of problems modified the method of forecasting, asking for likelihood assessments of positive/negative financial events. In P3 the respondents estimated the probability that their pension fund would earn more than 8% nominal return over the next 3 years. N3, on the contrary, asked for the likelihood of additional decrease, of 10% and more, in the telecommunication stock index over the coming 4 years.[11] Respondents were asked to circle their best estimate in 10% ladders, ranging from 0% to 100% (see Web supplement A).

To keep the field survey brief, we included only one anchored prediction assignment (henceforth: ANCHOR1), where participants predicted the national unemployment rate for March 2013, given the 6.5% rate in February 2012. We also borrowed problem #1525 from the US GALLUP investor optimism survey (http://www.ropercenter.uconn.edu), to control for macro-level expectations. Respondents were asked to classify their beliefs regarding the stock-market prospects for 2013 in one of five categories (1) very pessimistic (2) somewhat pessimistic (3) neither pessimistic nor optimistic (4) somewhat optimistic (5) very optimistic. In addition, we adapted a problem used by Ben Mansour et al. (2008), asking participants

[9] LOSS problems were derived from GAIN problems by subtracting or adding 100 NIS and changing signs to negative (except for GAINS4 and LOSSES4 that were similar).

[10] It is interesting to note that 61% of the respondents selected the safe lottery in GAINS4 or GAINS5, although it is easily verified that CRRA income maximizers must choose the risky option in both cases.

[11] The index lost about 20% in 2012 due to regulatory reform.

Table 3
Prediction assignments–field survey ($N = 75$).

Problem	General description	Domain	Mean (STD)	P10	P90
P1	Point prediction	Positive	7.8 (8.2)	2	12
N1	Point prediction	Negative	7.8 (9.8)	0	20
P2	Stock selection and point prediction	Positive	12.3 (13.0)	2	30
N2	Stock selection and point prediction	Negative	4.8 (10.4)	−7	20
P3	Probabilistic assessment	Positive	36.0 (23.9)	10	70
N3	Probabilistic assessment	Negative	46.5 (24.9)	20	80
ANCHOR1	Point prediction with an anchor	Negative	7.4 (1.6)	6	8.5
GALLUP	Expected stock market performance for 2013 (GALLUP #1525)	–	2.8 (1.0)	2	4
Π(50%)	Expected WINs in 10 independent tosses (Ben Mansour et al., 2008)	–	5.0 (1.2)	4	6.5

Mean and STD are the average and standard deviation; P10 and P90 are the lower and upper deciles.

Table 4
Median split of nominal predictions by LRP.

	Positive domain			Negative domain		
	P1	P2	P3	N1	N2	N3
Risk-seeking ($N = 33$)	8.3	15.5	40.3%	6.99	1.0	39.1%
Risk-averse ($N = 30$)	5.9	9.1	29.7%	7.78	8.2	53.3%

The risk-seeking (risk-averse) are those with LRP > (<) 30%. The 12 respondents at LRP = 30% are ignored. Dark (light) shading is used in cases where equality is rejected at $p \leq 0.05$ ($0.05 < p \leq 0.1$).

to imagine 10 independent tosses of a fair coin, assuming they are paid 10 NIS each time the coin shows “heads”. Each participant estimated, “by his personal luck”, the number of times that “heads” would occur bringing the monetary reward. The notation Π(50%) is henceforth used to denote win-chance optimism by the coin-toss problem, with Π(50%) = 50 for rational respondents.[12]

Descriptive statistics for the nine predictions are provided at the right panel of Table 3. For the analysis, we linearly normalize each response into [0, 100] optimism index. The least optimistic, or most pessimistic, respondent is placed at zero, while the most optimistic, or least pessimistic, is placed at 100. The symbol PRED is henceforth applied to denote the normalized prediction. The normalization brings the different predictions into common terms and allows for direct comparison of regression coefficients. Average optimism scores are normalized again for consistency, using OPT6 to denote the anchor-free optimism index (by P1–P3; N1–N3). As optimism scores always spread over [0, 100], we occasionally interpret results in terms of percentile points, using the customary “pp” for abbreviation.[13] The letters LRP, for lottery risk preference, henceforth denote the proportion of risky choices in the 10 binary choice assignments.

3.4. Main result: risk-preference correlates with optimism

The relative optimism of risk-seeking participants first shows in simple correlation analysis. The Spearman rank correlation between OPT6 and LRP is positive 0.39 ($p < 0.01$) and illustrative regressions confirm that forecast optimism significantly increases with lottery risk-preference ($T = 3.16$; $p < 0.01$). The relative optimism of lottery risk-seekers also shows clearly in Table 4 where we contrast the nominal assessments of the risk-avert (LRP < 30%; $N = 30$) with those of the relatively risk-seeking (LRP > 30%; $N = 33$). The risk-tolerant show stronger optimism in positive domains (P1–P3) and weaker pessimism in negative domains (N1–N3), and equality is rejected at $p < 0.1$ (by Pitman test for between-sample comparisons) in 5 of 6 cases. The largest differences emerge in P2–N2 where the relatively risk-seeking expect 15% biannual return on leading banking stocks and modest 1% loss on the stocks of distressed food retailers, while the risk-averse expect only 9% return on the banking investments and significant 8% loss on the food-merchants stocks ($p < 0.01$, for both comparisons).[14]

3.5. Closer search for the best risk-preference measure

The 10 choice problems that comprised the risk-preference part of the questionnaire could be used to characterize individual attitude to risk in more than dozen plausible ways. At the very basic level, it is interesting to separate risk preference in gain-domain (LRP(G): the proportion of risky choices in GAINS1-GAINS5) and loss-domain (LRP(L): the respective proportion for LOSSES1-LOSSES5). Taking a conservative approach, we could also count the number of cases where each respondent

[12] Ben Mansour et al. (2008) use the coin problem to account for probability weighting in estimating the distribution of CARA coefficients in a sample of 1500 respondents. We borrow the problem to control for belief in “personal luck” when win-chances are 50%, similarly to our choice-tasks lotteries.

[13] Problem specific normalizations may affect aggregate scores (OPT6) although the problem-level correlations are unchanged, but our results appear robust: when predictions are converted into MEAN = 0, STD = 1 optimism scores, the aggregate correlations are almost identical.

[14] We henceforth constantly use the nonparametric Wilcoxon signed-rank test for within-sample comparisons and the Pitman test for between-sample comparisons. We always report Spearman rank correlations, testing monotonicity. The Pearson correlations are typically similar.

Table 5
Illustrative regressions on OPT6.

	I	II	III	IV	V	VI	VII	IIX
Intercept	34.7*** (4.2)	35.2*** (3.3)	42.1*** (3.9)	16.2 (21.1)	23.0** (10.2)	33.7*** (3.3)	–	–
LRP	0.36*** (0.11)							
LRP(G)		0.34*** (0.08)		0.29** (0.09)	0.30*** (0.09)	0.32*** (0.08)	0.34*** (0.075)	
LRP(L)			0.11 (0.09)					
GENDER				5.6 (5.0)				11.0** (4.8)
Π(50%)				1.7 (2.0)	1.2 (2.0)			4.1*** (1.3)
EDU				0.5 (1.2)				
GALLUP					2.7 (2.3)			5.1** (2.1)
PROF						12.7** (5.4)	12.4** (5.6)	16.8*** (5.8)
AGE							0.44** (0.19)	
MOOD							2.5*** (0.8)	
R^2	12.0%	20.4%	2.0%	22.8%	22.7%	25.3%	29.0%	20.9%

OPT6, LRP and GALLUP are measured in [0, 100] scale. GENDER = 1 if male and PROF = 1 for investment industry occupation. Other definitions are provided below. The table presents the estimated coefficients with the standard deviations in smaller brackets. Since some of the estimations do not include an intercept, we use $R^2 = 1 - \text{SSE/SST}$ throughout the table for consistency (Green, 2003).
Two-tail significance at is summarized using *** $p < 0.01$; ** $p < 0.05$.

preferred to take risk in GAINS1–GAINS2, where the safe option paid as much as the risky option, to characterize strong risk-preference in gain-domain, and similarly count the number of cases where the safe option was preferred in LOSSES1–LOSSES2 (although the risky option was cheaper) to characterize strong risk-aversion in loss-domain. Alternatively, instead of building on problems 1–2 in each sequence, we could approximate individual inclination to avoid risk in gain-domain by summing up the expected payoff that the respondent sacrificed to avoid risk in GAINS3–GAINS5, while adding up the additional expected loss that was taken in LOSSES3–LOSSES5 to approximate the intensity of risk-preference in loss-domain. The difference between the two last measures (or the two preceding measures based on problems 1–2 in each sequence) could also be used as a net measure of individual propensity to avoid (take) risk. A comprehensive analysis of these and other risk-preference measures, however, robustly revealed that the proportion of risky choices in gain-domain is the strongest predictor of OPT6, even when other determinants of personal optimism are controlled. The predictive power of LRP(G) moreover strengthens when GAINS1 (where only two participants selected the risky alternative) is ignored. We therefore redefine LRP(G) as the proportion of risky choices in GAINS2–GAINS5. The rank correlation between risk-preference and anchor-free optimism, with this scale, approaches 0.5 ($\rho = 0.47$; $p < 0.01$), and columns I and II of Table 5 show that explanatory power increases from about 12% to more than 20% when LRP is replaced with LRP(G). The positive correlation shows very clearly in Table 6, where the optimism score of the most risk-seeking participants is almost twice larger than the optimism of the relatively risk-averse (30 pp difference).

Column III of the regressions table, however, demonstrates that the tendency to take risk in loss-domain fails to predict forecast optimism. The negative results are robust and insignificant coefficients emerge for various alternative loss-side measures. Choices in gain and loss domains weakly correlate in our sample ($\rho(\text{LRP(G)},\text{LRP(L)}) = 0.2$; $p = 0.08$), which technically explains the large discrepancy in results. As some psychology studies suggest that optimism and pessimism are fundamentally different (Chang et al., 1997), we also test if loss-side risk-preference obtains stronger correlation with negative-domain forecasts. The correlation between LRP(L) and our negative-domain optimism score (based on N1–N3) however is only 0.16 compared to 0.44 correlation for LRP(G). Preceding research suggests that loss-domain preferences are less consistent within-subject and exhibit stronger diversity between-subject, relatively to gain-domain preferences (cf., Table 2 of Abdellaoui et al., 2013). In our survey, the larger diversity in loss-side decisions reflects in standard deviation 28% for LRP(L) compared to 23% for LRP(G). The stronger noise could mask the loss-side correlation with forecast-positivity.

Table 6
The increase in OPT6 with LRP(G).

LRP(G)	0%	25%	50%	75%	100%
N	24	22	18	9	2
Mean OPT6	34.8	44.2	52.4	62.6	62.7

Table 7
Financial domain optimism–correlation table.

	Π(50%)	GALLUP	LRP(G)
OPT6	0.28**	0.24**	0.47***
LRP(G)	0.39***	0.23*	
GALLUP	0.25**		

3.6. Side-analysis of risk preferences

Since gain-domain risk-preference alone explains about 20% of the variation in forecast-optimism, we explore the covariates of inclination to take risk, before proceeding with the analysis of optimism. As in many preceding studies (cf. Croson and Gneezy, 2009), the males in our sample show stronger gain-domain risk-preference than the females (mean LRP(G) 35.8% vs. 19.3%; $p < 0.01$), but the differences lose significance in loss-domain (mean LRP(L) 38.5% vs. 30%; $p = 0.24$). In addition, the background analysis shows that risk-preference positively correlates with win-chance optimism and years of formal education (EDU), and Probit regressions of LRP(G) on an indicator for gender, Π(50%), and EDU suggest that the effects are jointly significant ($T = 2.79$ for Π(50%); $T = 2.09$ for gender; $T = 1.80$ for EDU). When these three variables are appended to regression model II, however, LRP(G) shows robustness while all other coefficients are far from significance (column IV of Table 5). Direct comparisons confirm that the predictive power of GENDER, Π(50%) and EDU for forecast-optimism is rather weak.[15] The risk-preference variable accordingly subsumes the other covariates in the joint estimation.

3.7. Financial-domain optimism

Forecast optimism, GALLUP expectations, win-chance assessments and lottery risk-preference may be looked upon as distinct facets of financial-domain optimism. Table 7 indeed shows that the four measures pairwise positively correlate. While the correlations are statistically significant in all six comparisons, the strongest result emerges for OPT6 and LRP(G). Column V of the regressions table moreover demonstrates that GALLUP and Π(50%) are subsumed by LRP(G) in mutual estimations. The results for the risk-preference variable are robust ($T = 3.54$; $p < 0.01$), while GALLUP ($T = 1.2$) and Π(50%) ($T = 0.6$) are far away from significance. The weak results for macro expectations and win-chance optimism however could follow from the concise one-problem elicitation. The class MBA survey extended the control by including 10 macro survey problems and five win-chance assessments.

3.8. Illustrative regressions

Columns VI and VII of Table 5 display the reduced-form equations received in applying regressions with model-selection (henceforth: RMS) to trace the bottom-line significant predictors of forecast optimism across the sample.[16] Column VI discloses the results for the case where an intercept is included while VII allows for removal of the intercept for insignificance. The results for the risk-preference variable are stable, but the equation in addition reveals that optimism significantly strengthened with PROF, MOOD and AGE. While the relative optimism of our small sample of industry professionals ($N = 13$) may be incidental, and the evidence regarding the effect of age on optimism is generally mixed (You et al., 2009), many psychology studies agree that positive moods enhance optimism (e.g., Lewis et al., 1995). It is therefore intriguing to observe that the predictive power of lottery risk-preference for forecast-optimism does not deteriorate when MOOD is controlled. Column IIX of the regressions table, finally discloses the RMS results when the risk-preference variable LRP(G) is omitted from the list of possible effects. GALLUP, Π(50%) and GENDER show significance in the misspecified version, but the fit decreases by almost 1/3, from 29% to less than 21%.

3.9. Problem-level analysis

The left panel of Table 8 examines the correlations between risk-preference and forecast-positivity in each prediction problem separately.[17] The leftmost column tests for monotonicity using the Spearman rank correlation. The column titled "slope" presents the coefficient b in least squares estimations of $\mathrm{PRED} = a + b * \mathrm{LRP(G)}$. Since the normalized predictions always range over [0, 100], slopes can be directly compared to identify the problems where risk-preference plays relatively stronger role. For the third column of the table, we employed the RMS procedure to extract the variables that significantly affect the

[15] The 53 males appear more optimistic with mean OPT6 = 49 compared to 38 for the 22 females ($p = 0.04$), but regressions suggest that GENDER explains less than 6% of OPT6 variance. GENDER shows significance in survey II where the gender composition is more balanced.

[16] The procedure successively removes the least significant variables but reexamines the effects that were previously removed after each round, so that variables can reenter the model repeatedly.

[17] LRP(G) still shows the best fit in problem-level analysis. When LRP(G) is replaced by LRP(L) the coefficient is insignificant in all seven cases. The slopes for P3 and N3 (where respondents chose one of 11 likelihood levels) were calculated by least squares regressions, but we used Probit regressions with iterative model selection to derive the T statistics. See Web supplement D for details.

Table 8
Problem-level results.

	Statistics for LRP(G)			Disagreement measures	
	Correlation	Slope	*T*-statistic	NSTD	Interquartile distance/NIQD
P1	0.07	0.01	0.04	1.06	6/0.77
N1	0.25**	0.20**	2.78***	1.26	9/1.15
P2	0.16	0.15**	2.08**	1.06	11/0.90
N2	0.43***	0.24***	4.63***	2.18	12/2.50
P3	0.14	0.12	0.55	0.66	30/0.83
N3	0.28***	0.28**	2.59***	0.53	50/1.07
ANCHOR1	0.03	0.04	−0.59	0.21	2.5/0.20
OPT6	0.47***	0.34***	4.54***	–	–

The leftmost column presents the correlation between LRP(G) and PRED; slope is the estimated coefficient b in OLS estimation of PRED = $a + b$ * LRP(G); *T*-statistic refers to the coefficient of LRP(G) after iterated RMS removal of insignificant effects. NSTD is the coefficient of variation (NSTD = STD/MEAN). Interquartile distance is the difference between P75 (the upper quartile) and P25 (the lower quartile). NIQD is (P75–P25)/MEAN.

case-specific predictions at $p < 0.05$. An "include" option is utilized to estimate LRP(G) even when the variable does not meet the threshold significance. The *T*-statistic is presented at the table.

The results of the three forms of analysis are generally consistent and confirm that lottery risk-preference positively correlates with case-specific optimism. The correlations, slopes and *T*-statistics are positive throughout the table. The statistics are significant, at least in 2 of 3 columns, in P2, N1, N2 and N3. The results are weaker in P3, and completely dissolve in P1. Closer look at the predictions reveals that the response to P1 and P3 was relatively concentrated compared to more diverse replies to the other anchor-free problems. The interquartile distance for P1, for example, was about 1/3 smaller than the interquartile distance for the matching problem N1 (see the rightmost column of Table 8). Similar, large difference in interquartile distance is observed for P3 compared to N3.[18] The correlation between risk-preference and optimism therefore dissolved in cases where levels of disagreement were relatively low.

In line with H3, the case-specific results are generally weaker than the aggregate (see the replicated OPT6 results at the bottom of Table 8). In line with H2, the link between risk preference and relative optimism completely disappears in ANCHOR1. The response to the anchored prediction assignment was especially dense with almost 43% of the responses falling within 0.5% distance from the 6.5% anchor provided in the script. The coefficient of variation (henceforth NSTD = STD/MEAN) for ANCHOR1 was 0.21 compared to NSTDs of 0.53–2.18 for the anchor-free predictions. More generally, the predictive power of LRP(G) for forecast optimism appears to increase with disagreement statistics; e.g., the RMS *T*-statistic shows positive correlation $\rho = 0.75$ with NSTD ($p < 0.01$), while anecdotally showing perfect rank correlation $\rho = 1$ with the NIQD (the normalized Interquartile distance).

4. The class survey

4.1. Method

Questionnaire II extended the field study in four aspects: (1) We used 24 dissimilar binary-choice tables to measure risk-attitudes in finer scale. (2) Forecast optimism was characterized by larger pool of 25 diverse predictions. (3) The control for macro-expectations and win-chance optimism was expanded. (4) The survey was run in MBA classes using twice stronger incentives. The translated script is provided in Web supplement C. The next paragraphs discuss the main extra features more closely.

4.1.1. Risk-preferences

Fig. 1 displays 3 of the 24 choice tables that were used to discern individual attitude to risk. Each line, in each table, presents a binary choice between a 2-outcome lottery and some risk-free alternative. The risky lottery is fixed, while the risk-free amount stepwise increases from the minimal to the maximal lottery outcome. The instructions explained that choice should be trivial in the limit rows of each table, asking participants to clearly mark the "switch point" (Andersen et al., 2006) where they first prefer the certain amount on the risky alternative. Similarly to the field survey, we only used 50% probabilities and constructed eight loss-domain tables from the eight gain-domain tasks. In Fig. 1, for example, L1 is the negative copy of G1. In addition, we included eight mixed-payoff tables where the lottery could either pay positive or negative outcomes, as in Table M1. In devising the choice tables we attempted to create a diverse collection, to reduce the risk of schematic anchoring and stimulate independent deliberation of each table. The instructions explained that choices depend on personal tastes, illustrating the implications of choosing different switch points on some exemplar table. The

[18] The three most common predictions in P1 were 10 ($N = 15$), 5 ($N = 13$) and 4 ($N = 9$); compared to 10 ($N = 13$); 2 ($N = 10$) and 20 ($N = 8$) in N1. The most frequent assessments in P3 were 30% ($N = 12$), 40% ($N = 12$), and 10% ($N = 11$) compared to 30% ($N = 14$), 70% ($N = 13$), and 20% ($N = 12$) for N3.

Problem G1

The Lottery	Certain amount
500 or 300	☐ 300
500 or 300	☐ 320
500 or 300	☐ 340
500 or 300	☐ 360
500 or 300	☐ 380
500 or 300	☐ 400
500 or 300	☐ 420
500 or 300	☐ 440
500 or 300	☐ 460
500 or 300	☐ 480
500 or 300	☐ 500

Problem L1

The Lottery	Certain amount
-500 or -300	☐ -500
-500 or -300	☐ -480
-500 or -300	☐ -460
-500 or -300	☐ -440
-500 or -300	☐ -420
-500 or -300	☐ -400
-500 or -300	☐ -380
-500 or -300	☐ -360
-500 or -300	☐ -340
-500 or -300	☐ -320
-500 or -300	☐ -300

Problem M1

The Lottery	Certain amount
+400 or -100	☐ -100
+400 or -100	☐ -91
+400 or -100	☐ -66
+400 or -100	☐ -15
+400 or -100	☐ +35
+400 or -100	☐ +84
+400 or -100	☐ +109
+400 or -100	☐ +130
+400 or -100	☐ +167
+400 or -100	☐ +189
+400 or -100	☐ +204
+400 or -100	☐ +261
+400 or -100	☐ +310
+400 or -100	☐ +342
+400 or -100	☐ +400

Fig. 1. Choice-tables G1, L1, and M1.

Table 9
The matrix of prediction tasks.

		D1	D2	D3	D4	D5
T1	Long-run numeric prediction					
T2	Short-run numeric prediction					
T3	Likelihood assessment of positive events					
T4	Likelihood assessment of negative events					
T5	Recollection of past results					

The five domains are D1 – local stock market; D2 – Israeli economy; D3 – performance of selected stocks; D4 – US economy; D5 – commodity prices. In D3, respondents selected one of two familiar stocks (using different stocks in each problem) and either predicted its long-run (T1) or short-run (T2) return, estimated the likelihood that the selected stock would outperform (T3) or underperform (T4) the alternative, or assessed the selected stock return in 2008 (T5). The shaded boxes denote the anchored problems.

number of steps in the tables varied from 10 to 29, with half of the tables, in each domain, using fixed increments and the other half using varying steps (as in M1).[19]

4.1.2. The prediction tasks

We adopted a 5 × 5 matrix design with five types of prediction tasks (T1–T5) covering five separate domains (D1–D5), as summarized in Table 9. The symbol Ti-Di henceforth addresses specific problems by type and domain. The five problems of type T1 asked for numeric point-predictions for dates or periods stretching beyond June 2015. Since the data was collected in June 2012, more than 3 years before the earliest prediction date, we term these tasks "long-run numeric predictions". The forecast horizon was considerably shortened in T2, where the predictions did not surpass June 2013. We accordingly address these five problems as "short-run numeric predictions". As in the shorter survey we also elicited likelihood assessments of future financial or economic events. The five problems in T3 referred to positive events, while the five problems in T4 extended the examination to negative scenarios. The problems in T5 were different, asking respondents to recollect stock returns and growth or unemployment rates from the past. The motivation for including these tasks arrives from Psychology studies suggesting that optimistic individuals hold more positive views of past experiences (e.g., Busseri et al., 2009).[20] T5 tested if this dimension extends to recollection of economic outcomes.

To test hypothesis H2 more thoroughly, we provided one-sentence anchors in 11 of the 25 tasks (the shaded slots in Table 9). As in preceding analysis, responses and indices were normalized to [0, 100] optimism scales. OPT25 henceforth

[19] About half of the varying-increments tables were skewed to the left, in the sense the first line where the safe amount exceeded the expected lottery payoff was at the lower half of the table. The remaining tables were skewed to the right. Table M1, for example, is slightly skewed to the left.

[20] Neuroimaging studies, in addition, suggest that partially similar neural processes surface when subjects imagine the future and recall the past (e.g., Addis et al., 2007). For convenience, we loosely use "recollection" to address these tasks; "estimating past realizations" would be more precise.

denotes the general relative-optimism score; OPT14 is the anchor-free index; while OPT11 summarizes personal optimism by the 11 anchored responses.

4.1.3. GALLUP, MCSI and win-chance optimism

The class questionnaire expanded the control for macro expectations, using five GALLUP investor optimism items (problems #1523-#1527) and five customary problems from the Michigan Consumer Sentiment survey (henceforth abbreviated as MCSI).[21] The GALLUP and MCSI examine consumers' expectations regarding the economy and personal economic prospects. The response is qualitative and discrete; e.g., respondents mark their level of pessimism or optimism regarding the "business conditions" for the coming year in one of several categories. The survey measures are therefore essentially different from the precise numeric assessments that were collected in our core prediction tasks. In addition, we expanded the control for win-chance optimism, using five distinct scenarios with varying win probabilities. The extended set could identify participants that overweight win-chances lower than 50% or underweight win-chances higher than 50%, generally permitting tighter control for win-chance distortion.

4.1.4. Participants and incentives

The questionnaire was distributed in five small advanced MBA classes. Again we camouflaged the purpose of the study, asking participants to fill-in the booklet in running-order, without connecting to supplementary material. Participation time was not effectively constrained, but only few students took more than 50 min. Our final sample consists of $N = 73$ respondents.[22] The descriptive statistics at the right panel of Table 1 prove that the MBA sample is less diverse than the field sample in terms of age, education and economic well-being. About 50% of the respondents held professional investment-industry jobs at the time of participation, but only 26% had more than 1 year of experience. All respondents received an instant participation fee of 50 NIS, and an additional bonus (averaging at 34 NIS) was distributed at the end of May 2013. The instructions explained that the extra bonus would be derived from one choice or prediction, emphasizing that the expected bonus is 40 NIS but "accurate prediction" or "successful choice" may increase the amount to 100 and more.

4.2. General analysis

Again, we exhaustively explore the lottery-choice dataset to extract the risk-preference measure with strongest predictive power for forecast optimism. The winning index is interestingly similar to the measure that obtained the strongest results in the field study, in spite of the differences in method of elicitation. Tendency to take risk is separately characterized for each choice table in binary 0–1 scale. The participant is classified "strictly risk seeking", if the lottery is preferred to a certain payoff that strictly exceeds its expected payoff, at least once along the table. In Problem G1 (Fig. 1), for example, the expected lottery payoff is 400 and the risk free alternative first exceeds this amount at 420. The respondent is therefore classified as strictly risk-seeking if the selected switch-point is at 440 or higher. By similar reasoning, the participant classifies as strictly risk-seeking in L1, if the random loss of 500 or 300 is preferred to a sure loss of 380. The large increments in our discrete choice tables make the definition quite strong. To classify as strictly risk-seeking in G1, for instance, the respondent must prefer the lottery even when the risk-free alternative pays 5% premium. The margin is even higher in other problems; e.g., more than 11% difference in M1.[23] The background analysis however strongly supported this measure, showing that "weak risk-preference" fails to recognize the significant correlations (see Section 5). For convenience we keep using LRP for the main risk-preference measure, with LRP(i) denoting the proportion of cases where the respondent classifies as strictly risk-seeking in tables of type i = G, L, and M.

Table 10 discloses the proportion of strictly risk-seeking choices in each domain and the correlations across the three domains. Students' inclination to take risk is rather high, with 41% of the gain-domain choices classifying as strictly risk-seeking. As in the field survey, risk-taking significantly strengthens in loss-domain ($p < 0.01$), but the far-from-perfect correlations confirm that the respondents exhibit considerable variability in risk-preference over gains, losses and mixed gambles. The two rightmost columns of the table moreover reveal that the gain-domain index shows the strongest correlation with OPT25 and OPT14. When OPT25 is regressed on the three disjoint risk-preference indices, only LRP(G) obtains a significant coefficient ($T = 2.06$; $p = 0.04$, see Column I of Table 11). Significance climbs to $p < 0.01$ ($T = 2.67$) when optimism is measured by the 14 anchor-free problems (Column II), but completely diminishes ($T = 0.11$) for OPT11 (Column III). A median

[21] http://www.sca.isr.umich.edu. Similar problems are customarily included in the British Household Panel Survey (BHPS); see https://www.iser.essex.ac.uk/bhps. MCSI classifies respondents' sentiment in 2–3 categories (e.g., asking if they expect "better times", "worse times", or "about the same times"), our adapted version expanded the choice set into six categories (see supplement C).

[22] Six participants were instantly filtered for extreme inconsistency in choices. The formal criterion was more than 80% distance in switch points for same domain problems; e.g., ticking switch line 2 in G1 (extreme risk aversion) but choosing the last switch line (extreme risk preference) in G2. We used four versions of the questionnaire, with series of six choice assignments (two gain-domain; two dissimilar loss-domain and two mixed-payoff) separating short blocks of prediction tasks – see supplementary appendix C for details. The positive correlation between LRP(G) and forecast-optimism shows in all four versions.

[23] The loss of information brought by binary choice tables is discussed at Andersen et al. (2006). In G1, for example, those switching at 420 may be risk-neutral that randomly selected the lottery at the indifference point. Participants with indifference points in (400, 420) thus cannot be classified as "strictly risk-seeking" although they fall into the category by standard definitions.

Table 10
Risk-preference over gains, losses and mixed lotteries.

	Mean (N = 73)	Correlations			Correlation with OPT25	Correlation with OPT14
		LRP(G)	LRP(L)	LRP(M)		
LRP(G)	41%	1	0.55***	0.70***	0.32***	0.42***
LRP(L)	67%		1	0.55***	0.20*	0.19
LRP(M)	46%			1	0.20*	0.30**
LRP	51%	0.89***	0.77***	0.88***	0.30**	0.37***

Table 11
Illustrative regressions on optimism scores.

Model	I	II	III	IV	V	VI	VII	IIX
Dependent	OPT25	OPT14	OPT11	OPT25	OPT14	OPT11	OPT14	OPT14
Intercept	41.9***	30.7***	50.2***	–	–	–	–	–
	(5.0)	(5.4)	(5.3)					
LRP(G)	0.20**	0.27***	0.01	0.20***	0.27***	0.05		–
	(0.09)	(0.10)	(0.10)	(0.05)	(0.06)	(0.06)		
LRP(L)	0.03	−0.04	0.10					
	(0.08)	(0.09)	(0.09)					
LRP(M)	−0.04	−0.00	−0.08					
	(0.11)	(0.11)	(0.11)					
MCSI				0.33***	0.35***	0.28***	0.46***	0.40***
				(0.08)	(0.09)	(0.09)	(0.11)	(0.10)
GALLUP				0.30***	0.06	0.53***	0.18	0.16
				(0.09)	(0.11)	(0.11)	(0.12)	(0.12)
GENDER				10.7**	8.7*	10.3**	11.9**	12.5**
				(4.1)	(4.6)	(4.6)	(5.0)	(5.1)
WLRP(G)							0.19*	
							(0.09)	
R^2	10.8%	16.2%	1.9%	31.8%	27.4%	14.3%	12.6%	7.6%

OPT25, OPT14, OPT11, LRP, WLRP, GALLUP and MCSI are measured in [0, 100] scale. GENDER = 1 if male. The table presents the estimated coefficients with standard deviations in smaller parentheses. The intercept is included only when statistically significant at $p < 0.1$ with $R^2 = 1 - \text{SSE/SST}$ for consistency.

split reveals more than 20 pp difference in anchor-free optimism of the relatively risk-averse compared to the risk-seeking (mean OPT14: 30 vs. 51; $p < 0.01$).

Column IV of Table 11 presents the OPT25 regression results after iterated removal of insignificant effects. The risk-preference coefficient is statistically significant at $p < 0.01$, even with extended control for macro-expectations. When the 10 GALLUP and MCSI responses are normalized and averaged to construct a global SURVEY optimism score, SURVEY shows positive, marginally significant, correlation with OPT25 ($\rho = 0.20$; $p = 0.09$), while exhibiting close to zero correlation with risk preference ($\rho = 0.01$ with LRP(G)). Columns V–VI of the regressions table illustrate that gain-domain risk-preference is the strongest predictor of anchor-free optimism in the MBA dataset, similarly to the field study results, but the correlation suspends when an anchor is provided.[24]

Out of more than dozen personal attributes, only GENDER showed significant effect on forecast optimism in the class survey (columns IV–VI of Table 11). As in several preceding studies (cf. Jacobsen et al., 2014), our $N = 29$ female participants appear less optimistic than the males. The mean OPT25 of the females was about 43 compared to almost 55 for the males ($p = 0.02$). More than 65% of the females were relatively pessimistic with OPT25 < 50, while almost 60% of the males showed OPT25 > 50. Again, the males seek risk more than the females (mean LRP(G) 44% vs. 36%), but the MBA differences are not large enough for significance ($p = 0.35$).[25] The insignificant results for other predictors of optimism (such as MOOD and AGE that showed significance in the field survey) could follow from the relative uniformity of the student sample.

Column VII of Table 11 illustrates that the fit of the regressions decreases by more than 50% (from 27.4 to 12.6) when risk-preferences are measured using weak definition (WLRP(G)) instead of the strict LRP(G) discussed above. For the weak definition, say the respondent exhibits "strict risk aversion" if a certain payoff that is strictly lower than the expected lottery payoff is preferred to the lottery, and classify the respondent "weakly risk-seeking" when she does not exhibit strict risk

[24] Only two MCSI and two GALLUP problems significantly correlated with OPT25 (OPT14). The relevant MCSI items were those where respondents predicted the national economic conditions for the next 1 or 5 years. The significant GALLUP items dealt with the inflation-rate and stock market performance. We report the results for the respective GALLUP and MCSI scales. As in the field survey, win-chance optimism did not mediate the correlation between forecast-optimism and risk-preference; ρ(LRP(G),OPT14) rises to 0.56 for the 33 respondents with $\Pi(50\%) = 50$ (no win-chance distortion).

[25] Side analysis of risk-preferences did not provide additional insights. The positive correlation between risk-preference and optimism emerges for males ($\rho = 0.52$; $N = 44$; RMS T-statistic = 4.5) and females ($\rho = 0.15$; $N = 29$; RMS T-statistic = 2.4).

Table 12
Task-specific results.

Task type	Domain					OPT by anchored tasks	OPT by anchor-free tasks
	D1	D2	D3	D4	D5		
T1	0.23**	0.07	0.31***	0.18	−0.23*	−0.12	0.33***
	0.15***	0.04	0.14**	0.05	−0.09	−0.05	0.16***
	2.82***	−0.01	2.61**	1.79*	−1.59	−1.16	3.24***
T2	0.24**	−0.10	0.23**	0.07	−0.12	−0.14	0.30***
	0.07	−0.06	0.14**	0.06	−0.06	−0.07	0.13**
	1.42	−0.77	3.04***	1.09	−1.10	−1.32	1.86*
T3	0.07	0.22*	0.23*	0.12	−0.05	0.10	0.21*
	0.08	0.19**	0.15*	0.13	0.01	0.10	0.15**
	1.03	2.26**	1.60	0.92	−1.58	1.27	1.94*
T4	0.14	−0.11	0.08	−0.12	0.01	−0.05	0.11
	0.10	−0.07	0.00	−0.07	0.04	−0.02	0.02
	0.96	−0.84	1.19	−0.44	0.65	−0.45	1.08
T5	0.23**	−0.03	0.25**	0.17	0.17	0.11	0.42***
	0.07	−0.06	0.08	0.06	0.11	0.06	0.11**
	1.43	−0.66	1.59	1.39	2.17**	0.90	2.61**
OPT by domain	0.39***	0.06	0.38***	0.16	0.05	−0.01	0.42***
	0.23***	0.03	0.19***	0.09	−0.01	0.01	0.25***
	3.46***	0.35	3.70***	1.06	0.20	0.17	4.23***

The left panel of the table tests the strength of the correlation between risk-preference and forecast optimism at the case-specific level. Each box presents, from top to bottom, the correlation, slope and T-statistic as defined in Table 8. The anchored tasks are shaded. The right panel contrasts the results for anchored and anchor-free optimism indices, controlling for the type of prediction tasks. The problem-level RMS equations are disclosed in Web supplement E; the disagreement indices (similar to Table 8) are presented in Web supplement F.

aversion.[26] Let WLRP denote the proportion of tables where the participant classifies as "weakly risk-seeking", with WLRP(G) denoting the respective gain-side proportion. The correlation between WLRP(G) and LRP(G), with this definition, is far from perfect ($\rho = 0.44$), suggesting that the weak and strict measures are quite distinct. The correlation between WLRP(G) and OPT14 is only 0.25, compared to the 0.42 result for LRP(G). The twice stronger results for the strict risk-preference measure reinforce the trait interpretation: decision-makers that clearly chase risk in plain lottery-choice assignments tend to see the bright side in quantitative financial prediction. Column IIX of the regression table finally illustrates that the omission of risk-preferences altogether from the regressions decreases explanatory power further to 7.6%.

4.3. Task-level analysis

To close the analysis, we briefly examine each type of predictions separately, discussing the additional insights regarding the scope of personal optimism.

Numeric predictions: Hypotheses H1–H3 are already met in the long-run numeric predictions (row T1 on top of Table 12). Optimism increases with risk-preference in all anchor-free tasks, but the positive correlations disappear and even reverse in the anchored assignments. The correlations appear stronger on the aggregate ($T = 3.2$, compared to 1.8–2.8 for specific predictions).

The results generally weaken in the short-run predictions. Row T2 of the table reveals that risk-preference and short-run optimism significantly correlated only in D3, where respondents forecasted the performance of specific stocks. Significance dissolved in the other anchor-free tasks (D1 and D4), where the prediction target was the few months' performance of major stock indices. Since the indices are less volatile than underlying stocks, the comparison informally illustrates that personal optimism may not be strong enough to reflect in prediction of low-volatility targets.[27]

The negative T-statistics in the shaded T1–T2 boxes of Table 12 are puzzling, as they suggest that optimism could decrease with risk-preference when respondents receive a usable anchor. Indeed, when the four numeric anchored predictions (T1-D2; T1-D5; T2-D2; T2-D5) are aggregated to derive a restricted optimism scale, the resulting index negatively correlates with gain-domain risk preference ($\rho = -0.20$; $p < 0.1$), and GLS estimations (a system of two equations) confirm that the risk-preference coefficient changes signs from positive to negative in anchor-free vs. anchored numeric predictions (T-statistic 3.5 for anchor-free optimism vs. −1.4 for anchored optimism; WALD = 11.2; $p < 0.01$). Trying to understand the puzzle we

[26] In G1, for instance, the respondent classifies as strictly risk averse if the switch line is at payoff ≤ 380, thus classifying as weakly risk seeking when the switch line is at payoff ≥ 400. Switch lines were equal or closest (from above) to the expected lottery payoff in 31% of the gain-domain choices (e.g., in G1, 57.5% switch at level ≥ 440 but 31.5% switch at 400 or 420). This explains the weak correlation.

[27] Macroeconomic survey studies demonstrate that forecast uncertainty tends to diminish as prediction horizons shorten (e.g., Engelberg et al., 2009). We did not control for prediction horizon in the current study since the elicitation of short and long-run predictions for the same stock could bias the risk-preference and optimism relation.

learn that the risk-avert show tendency to place their predictions closer to the anchor. Using the absolute relative deviation, |DEV| = |prediction − anchor|/anchor as the distance metric, we find positive correlation 0.27 ($p = 0.02$) between LRP(G) and average |DEV|, and RMS estimations confirm that the tendency of risk-averse respondents to place their forecast around the anchor extends beyond other possible |DEV| determinants ($T = 2.37$; $p < 0.01$). By way of interpretation, the risk-averse could "turn to the anchor", as a reasonable or safe prediction strategy. Incidentally, this reversed the sign of correlations in some scenarios.

Likelihood assessments: The stronger optimism of risk-seekers still shows when respondents estimate the likelihood of future economic or financial events in discrete 10% steps. The results appear rather weak in Table 12, but statistical power is enhanced when (anchor free) pessimism by T4 is subtracted from optimism by T3, using the difference Δ(T3–T4) as the dependent variable for the analysis. The correlation between Δ(T3–T4) and LRP(G) is 0.26 ($p < 0.03$) and a median split reveals mean Δ(T3–T4) of more than 16% for the relatively risk-seeking compared to only 5% for the risk-avert ($p < 0.01$). Regressions with model selection confirm that net optimism increases with risk-preference when other predictors are controlled; the T-statistic of LRP(G) is 3.09 ($p < 0.01$). When parallel analysis is run for the anchored optimism-minus-pessimism index, the respective T-statistic is only 0.94.[28]

Recollection tasks: The optimistic outlook of risk-seekers also shows in recollection of particular past events. When participants estimate the 2000–2010 return on industry stocks (T5-D1), for example, the average estimate of the relatively risk averse is about 33.5%, compared to 3-times larger 108% for the risk-seekers ($p = 0.02$). The estimations moreover suggest that optimism could strengthen with risk-preference even in anchored recollection tasks. When the normalized T5-D4 and T5-D5 responses are averaged to construct a restricted anchored-recollection optimism scale (T5-D2 is omitted since the problem referred to local growth rates which are historically stable) the correlation with LRP(G) is 0.19 and the RMS T-statistic is 2.3 ($p = 0.02$), proving the optimism increased with risk-preference in spite of the provision of anchors. Intuitively, the anchors could play weaker role in these assignments (cf. Sugden et al., 2013) as the weight of private impressions increases on the expense of exogenous anchors in strong uncertainty recollection tasks.

Domain-level anchoring: The hypothesized anchoring effect nicely reflects at the bottom line of Table 12 where we summarize the results for the five domains. The correlations between risk-preference and domain-optimism are strong and significant in D1 and D3 where subjects did not receive usable anchors, but completely deteriorate in D5 where all five problems were anchored. We are quite convinced that if the anchoring was applied to D1 or D3, reformatting D5 as "anchor free", the patterns of significance would reverse.

Disagreement and optimism scope: The collection of 25 problems, including 11 anchored, permits more thorough examination of the link between disagreement and optimism. The data first shows that the anchors have decreased disagreement regarding the target. The spread of predictions around the mean is more than 50% smaller for the anchored tasks (mean NSTD 0.48 compared to 1.05 for the anchor-free tasks; $p < 0.02$), and the anchor-free predictions first order dominate the anchored predictions in terms of NSTD (and NIQD) distributions. In accordance with H2, the correlation between risk-preference and optimism dilutes in parallel. The mean RMS T-statistic for the anchor-free tasks is 1.6 compared to −0.09 for the anchored predictions ($p < 0.01$). Closer look into the 14 anchor-free predictions still reveals mild increase in correlations with disagreement, but the differences are far too weak for significance (e.g., 0.2 Spearman correlation between NSTD and T-statistic; $p = 0.42$). The relatively weak results here may follow from the use of 14 diverse prediction targets. The effects of uncertainty on optimism-correlations could show more clearly in judgmental forecasting experiments where investors predict returns from anonymous historical series (Sonsino and Regev, 2013), but this falls beyond the goals of the current study.

4.4. Online LOT-R survey

While devising the field and class surveys we chose to avoid personal optimism questions and the LOT-R test in particular, suspecting that if responders identify the survey as an optimism study, self-classifications may jointly lead to increased risk-taking and positive forecasting (or vice versa), boosting the hypothesized correlations. To address referee comments on the absence of LOT-R, we approached the class survey respondents again in June 2014, about two years after the original survey, asking for participation in a brief on-line continuation study. The invitation message explained that 1 of each 5 participants would receive a bonus of 100 NIS, directing the former students to an online Google form. In addition to the 10 customary LOT-R problems, the short questionnaire included two control questions aimed at characterizing possible shifts in personal optimism over the two years since the original survey.[29] Unfortunately, only 36 of the 73 students that took the class survey filled-in the Internet questionnaire. The LOT-R scores of the respondents were similar to those observed for MBA students in other studies (mean LOT-R 16.1) and their forecast-optimism and risk-preference were not significantly different from

[28] Alternatively, the results for T3–T4 strengthen when the 13 respondents in opposite optimism quartiles (classifying as 25% most optimistic in T3 and 25% most pessimistic in T4 or vice versa) are removed. The T3 correlation increases to 0.28 and the T-statistic climbs to $T = 2.4$ ($N = 60$; $p < 0.02$). The T4 correlation becomes 0.13 and T rises to 1.28 ($p = 0.2$). In terms of the survey design literature, these respondents may exhibit an acquiescence bias (Messick and Jackson, 1961), tending to either agree or disagree with the printed statements independently of the contents.

[29] Respondents classified their last 2 years experiences and the change in their expectations for the future in five categories. The LOT-R correlations with optimism and risk-preference do not change when LOT-R is corrected for the controls. Details on the online survey are provided in Web appendix G.

Table 13
LOT-R results ($N = 36$).

Panel A: correlation table			Panel B: regressions on OPT14*				
	OPT14	LOT-R	LRP(G)	LOT-R	MCSI	Gender	R^2
LRP(G)	0.27	0.21	0.17(0.11)	0.05(0.14)	0.37**(0.12)	13.3*(7.2)	33.5%
OPT14	–	0.10					

GALLUP was removed for insignificance (see model V of Table 11).

those of the 37 that did not respond. The 50% decrease in sample size, however, strongly reduced statistical power and the correlation between anchor-free optimism (OPT14) and gain-domain risk-preference diminished to $\rho = 0.27$ ($p = 0.11$), compared to $\rho = 0.42$ ($p < 0.01$) for the complete pool. The correlation between OPT14 and LOT-R, however, was much weaker $\rho = 0.10$ and far from significance ($p = 0.57$). At the right panel of Table 13 we report the regression results for OPT14 (similarly to model V of Table 11), when LOT-R is included as explanatory variable. The hypothesis LRP(G) = 0 can be one-side rejected for LRP(G) > 0 in spite of the small sample size, while the LOT-R effect is clearly rejected ($T = 0.38$). Interestingly, LOT-R shows significant 0.37 correlations with $\Pi(50\%)$ ($p < 0.02$), while showing 0.21 (0.31) correlation with gain-domain (loss-domain) risk-preference ($p = 0.22$ and $p = 0.07$ respectively). The sample size of the repeated survey is too small for definite conclusions, but it is interesting to observe that LOT-R optimism does not mediate the correlation between forecast-optimism and risk-preference, although risk-preference tends to increase with LOT-R. By way of interpretation, the results suggest that optimism with regard to personal life-course events should be separated from financial-domain optimism (where the latter jointly reflects in stronger propensity to take lottery-risk and positive outlook for future economic uncertainties).

5. Discussion

Formal definitions of ambiguity aversion frequently control for subjective expectations, saying the decision-maker is ambiguity averse if the risky prospect is preferred to the ambiguous counterpart. Abdellaoui, Baillon, Placido and Wakker (2011; henceforth ABPW) run multi-phase laboratory experiments, where spaces of uncertainty (e.g., future CAC40 performance) are split into equiprobable events, and subjects expose, in series of binary choice decisions, their certainty equivalents of standard lotteries and subjectively equivalent ambiguous prospects. Pessimism in choice under risk, by ABPW results, almost perfectly correlates with pessimism in choice under ambiguity (0.78–0.86 correlation in formal pessimism indices), even though pessimism is generally stronger for sources of ambiguity. Applying our main hypothesis H1 to the ABPW framework, we would expect that the equiprobable cutoff levels that subjects reveal for positive events, such as the return on CAC40, would increase with individual inclination to take risk when chances are known. Since Abdellaoui et al. (2011) only study one source of economic uncertainty (CAC40 performance in May 31, 2006) and our nonparametric approach basically builds on aggregate examination of optimism with respect to distinct sources, we did not attempt to test H1 on ABPW's data. The 2011 paper "source methodology" could, in principle, be utilized to examine more closely the two-level link between individual risk-preference and willingness to take risk under uncertainty. In particular, such experiments could be used to test the three-ways correlation between positivity of uncertain beliefs (as reflected by the equiprobable cutoff levels that subjects reveal for diverse economic uncertainties) and pessimism indices for risk and ambiguity. An obvious drawback is that the source methodology, as applied at the Abdellaoui et al. (2011) experiments, already demanded almost 2 h interviews, for only three sources of uncertainty. The testing of more than few uncertainties in a single interview appears challenging.[30]

At the practical level our results propose that concise gain-domain risk-preference questionnaires may be used, as psychometric tools, to identify individuals that are susceptible to unrealistic expectations, especially in domains of high uncertainty. Too cautious long-run saving-decisions of risk-averse individuals may be expectations driven and consultation or financial education can improve if such investors are confronted with empirical evidence or are forewarned regarding their inherent tendency for pessimistic views.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jebo.2014.10.002.

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[30] Such experiments could also be used for testing individual heterogeneity with respect to the documented effects. As pointed out by a referee, individuals may – for example – be relatively realistic in expectations while showing strong aversion to risk and ambiguity.

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