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Abstract: Risk is ubiquitous in agriculture and a core interest of agricultural economists. While farmers' risk preferences are well studied, there is limited knowledge on the perspectives of other stakeholders on farmers' risk preferences. We address this gap by eliciting predictions for a multiple-price-list task from 561 students, farm advisors, and experts from Italy, Poland, Croatia, Spain, France, Sweden, and the Netherlands. First, we investigate whether the risk preferences of farmers from different European production systems differ in terms of predictability for the experts. Second, we compare the predictions of different groups of experts, as well as their accuracy. Third, we evaluate whether the accuracy of predictions can be improved by changing incentive mechanisms. Overall, we find substantial variation in individual predictions. Yet, average predictions are close to the averages of the observed responses of farmers. We find that an international group of researchers in experimental economics provides more accurate predictions than farm advisors and other experts or students of agriculture. Differences in predictions by production systems are small. Incentivizing predictions by either a tournament scheme (the best prediction receives a reward) or high accuracy (randomly selected participants are paid depending on the quality of their prediction) do not strongly affect the accuracy, but may slightly reduce noise in the predictions.

Keywords: Risk attitudes, Expert predictions, Expert forecasts, Multiple prices lists, Meta-science, Experimental economics

JEL codes: Q19, D81, C99

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1 Introduction

Predictions of research results by experts can improve the effectiveness of the research process in the social sciences for at least three reasons (DellaVigna et al., 2019). First, predictions offer a systematic way to elicit a community's ex-ante beliefs on a study, alleviating hindsight bias. Establishing a clear benchmark for what is known on what and by whom in combination with a debriefing can help to update experts' beliefs which increases the effectiveness of the research process. Second, a benchmark of what experts predict ex-ante can facilitate the acceptance of null results in particular when the null deviates from experts' views. Third, systematic and regular predictions from an expert community can facilitate more accurate predictions. Said predictions can inform future research designs, for instance when selecting treatments for designing effective behavioral interventions (DellaVigna and Pope, 2018a; Milkman et al., 2022). Furthermore, it has been shown that prior beliefs of experts and policy-makers can differ (Vivalt and Coville, 2022), i.e., expert predictions can provide new information to policy-makers, leading to an update of beliefs.

In agricultural economics, the study of farmers' risks preferences is a foundational issue (Iyer et al., 2020). Starting from early work (Binswanger, 1980), experimental techniques to determine farmers risk preferences have become a widely used approach (recent examples are Bellemare et al., 2020; Bonjean, 2022; Palm-Forster et al., 2019). A comprehensive review the development of the literature on risk preferences in context of European agriculture is given by Iyer et al. (2020). This research is generally considered important to improve the understanding of farmers' behavior, as preferences towards risk influence decisions in many domains, not only with respect to price and production risks, but also the uptake of new technologies and farming practices (Dessart et al., 2019).

Predictions of research results in economics have often focused on laboratory experiments (DellaVigna and Pope, 2018b, 2018a). In agricultural economics, predictions of experimental outcomes have focused on narrow topics such as the behavior of German farmers under different treatments of a public goods game (Rommel et al., 2022b), using professional academics and graduate students as experts. To the best of our knowledge, there is no comprehensive study eliciting expert knowledge about an important topic such as risk preferences in European agriculture (Iyer et al., 2020), providing insights on country-specific expert predictions as well as the potential of financial incentives for their improvement.

The first objective of this study is to understand whether the ease to predict farmers' behavior is context-dependent, i.e. differs for farmers with different farming backgrounds. Farmers from eight farming systems, whose behavior was to be predicted, took part in an incentivized multiple price list (Tanaka et al., 2010) based on economic gambles to elicit their risk preferences (including wine growers in Croatia, olive farmers in Italy and Spain, potato growers in France as well as arable farmers in the Netherlands, Sweden, and Germany). By varying topical expertise and local context knowledge in our samples of forecasters, our analysis can focus on whose predictions are most accurate for whom. Here we will consider both the average accuracy of predictions, as well as the variance of accuracy. In other words, we want to assess whether the predictive accuracy differs by production system, as this allows us to evaluate in which cases experts may "fill-in" for farmer data or in which cases their priors are far from the reality.

The second objective of this study is to present results from a cross-country prediction study of farmers' risk preferences. Simply put, we investigate who knows what about risk preferences of farmers. Multiple samples of more than 500 experts in total (Polish, French, Croatian, and Italian farm advisors; Swedish students of agriculture; a group of mixed experts from Spain; as well as experimental economists and a group of experts with mixed backgrounds) predicted the outcomes of risk preference elicitations of farmers from each farming system.

The third objective of this study is to improve the understanding of how to incentivize accurate predictions through the experimental design. Previous research on expert predictions has focused on the impact of elicitation formats. Notably, DellaVigna et al. (2020) tested the impact of (1) reference values, (2) raw units vs. standard deviations, (3) sliders vs. text entry, and (4) different slider bounds had on expert evaluations, finding that only slider bounds have had a small impact on predictions. We augment this line of research by focusing on another important question: the role of financial incentives. Financial incentives are commonly used to motivate careful decision-making in economic experiments (Camerer and Hogarth, 1999; Voslinsky and Azar, 2021), which corresponds to making accurate productions in this study. Specifically, by randomly assigning participants to one of five conditions in a between-subjects design, we test two tournament scheme incentives against two random incentivized systems (Charness et al., 2016; Clot et al., 2018) and a control treatment. One in 50 participants is selected for a payment. In treatments 1 and 2, this selection happens in a tournament scheme with a low, respectively high reward. In treatments 3 and 4 the random incentivization of accuracy is independent of what others do and solely depends on the deviation from the actual outcome (here with a low, respectively high penalty for inaccurate predictions). In treatment 5 we randomly pay a fixed price to participants independent of their predictions.

In the next section, we will introduce the data collection process, experimental design and the methods used for the analysis. Then, we present and discuss the results in sections 3 and 4. In the final section, we present some conclusions.

2 Data collection, experimental design, data and approach for data analysis

2.1 Data collection

Data were collected through an online survey between 15 December 2021 and 28 January 2022. The survey was available in multiple languages (Croatian, English, French, German, Italian, Polish, and Spanish) and distributed through multiple channels, including research networks of the authors, advisor associations, and students. Apart from international researchers, data was particularly collected in countries for which predictions were gathered in the experiment. As a sufficient number of observations was lacking for all countries, we ended up with eight different expert groups (farm advisors from Poland, Croatia, France and Italy, mixed experts from Spain, Swedish agricultural students, International researchers, and a group of mixed experts ("Other") from different countries and with different backgrounds). After the participants were welcomed and introduced to the survey's objectives, informed consent was obtained. Predictions were explained and elicited at the beginning of the survey. Depending on the treatment, the incentive mechanism was introduced. In a later part of the survey, participants were asked to select the assigned incentive mechanism from a list of all applied mechanisms, in order to understand whether it was salient and well-understood by the participants. Finally, socioeconomic information about the participants, as well as their assessment of the prediction task (e.g. perceived difficulty, confidence in the predictions) were collected.

Table 1: Descriptive Statistics of the participants

	(N = 561)
Age	
Mean ± Standard Deviation	38.26 ± 11.92
Median	37
Min	20
Max	84
Female	
If respondent is female	240/555 (43.2%)
Professional background	
Economics or Business Studies	184 (32.8%)
Agricultural Sciences/Farming	238 (42.4%)
Other	139 (24.8%)
Sample	
Polish farm advisors	109 (19.4%)
Croatian farm advisors	56 (10.0%)
French farm advisors	72 (12.8%)
Italian farm advisors	51 (9.1%)
Spanish experts	59 (10.5%)
Swedish students	69 (12.3%)
International researches	76 (13.6%)
Other	69 (12.3%)

Source: Own calculations

We obtained informed consent from all participants. Participants were offered a debrief by allowing them to subscribe to a short summary of the research results. We pre-registered basic analysis before data collection (see https://aspredicted.org/Z8Z_FV7). In total, 561 participants completed the survey. Each respondent predicted the outcomes of all eight samples, the final dataset contains 4,488 predictions. Summary statistics of the sociodemographic characteristics of the participants are presented in Table 1.

2.2 Experimental design

The to-be-predicted data from farmers were gathered as part of a large-scale cross-country effort to replicate the study of Bocquého et al. (2014) in different European Union member states (see Rommel et al. (2022a) for details). In this study, which took place in the second half of 2021, farmers had to choose between riskier and safer options in a modified version of the risk preferences elicitation task of Tanaka et al. (2010). Monotonous switching was enforced in this study, i.e., farmers could only indicate a single switch from option A to option B. The data collection for the prediction study took place after the farmer data were collected but before the outcomes of farmers' choices were known (in late 2021 and early 2022). Authors of the replication study were not allowed to take part in the prediction.

Table 2: Multiple price list used in this study and difference in expected value

Row	Option A		Option B		Expected payoff difference (A – B)
Series 1	*Probability 30%*	*Probability 70%*	*Probability 10%*	*Probability 90%*	
1	400	100	680	50	77
2	400	100	750	50	70
3	400	100	830	50	60
4	400	100	930	50	52
5	400	100	1060	50	39
6	400	100	1250	50	20
7	400	100	1500	50	– 5
8	400	100	1850	50	– 40
9	400	100	2200	50	– 75
10	400	100	3000	50	– 155
11	400	100	4000	50	– 255
12	400	100	6000	50	– 455

Note: Adapted from Tanaka et al., 2010; Displayed units are experimental currency units.

For each of the eight farmer samples (wine growers from Croatia, olive farmers from Italy and Spain, potato growers from France and arable farmers from the Netherlands, Sweden, and Germany), we asked experts to predict the average of the row after which farmers in a specific sample would switch from the safer option A to the riskier Option B, for one of the multiple price lists of the risk elicitation task of Tanaka et al. (2010)[1]. Hence, higher numbers indicate higher predicted average risk aversion. Farmers choosing the safer option A seven times (i.e. switching after the sixth row) or more are risk averse. We elicited predictions on a scale from 0 (farmers on average never choose the safer option A) to 12 (farmers on average always choose the safer option A). This format was perceived as the most intuitive by the research team. Predictions of means had to be entered with a one decimal point accuracy on a slider for each

[1] Participants only predicted one of three lists in order to reduce the complexity of the overall prediction task (i.e. that participants only had to carry out 8 instead of 24 predictions; in addition, the focus of the study was on risk, whereas the original task also aimed at loss aversion and probability weighting).

of the eight samples. Table 2 displays the price list, including the expected payoff difference (which was shown neither to forecasters nor farmers participating in the original study).

Table 3: Overview of the experimental treatments

Row	Type	Selection criterion for Payment	Payable amount
ACCLOW	Accuracy	Randomly selected	€ 300 – the squared deviation of the prediction from true value
ACCHIGH	Accuracy	Randomly selected	€ 300 – two times the squared deviation of the prediction from true value
TOURHIGH	Tournament	Most accurate prediction	€ 300
TOURLOW	Tournament	Most accurate prediction	€ 100
CONTROL	Control	Randomly selected	€ 300

Our main outcome variable of interest is the accuracy of the predictions, defined as a predictor's absolute deviation from a sample's actual average. Note that this definition implies that *smaller* values (lower bound at zero) indicate predictions with *higher* accuracy. Recall that we obtained eight predictions per participant (one for each farmer sample). Accurate predictions were incentivized in four out of five treatments, which were implemented between subjects (see Table 3 for an overview). In treatment ACCLOW, one randomly selected participant from a group of 50 participants was offered a payment calculated as 300 Euro minus the squared deviation of one randomly selected prediction out of the total of eight predictions per participant. In treatment ACCHIGH, the payment was calculated as 300 Euro minus twice the squared deviation in order to test for incentive effects, i.e., in ACCHIGH deviations were punished relatively more. In TOURHIGH and TOURLOW (the two tournament schemes), payments of 300 and 100 Euro were offered to the best prediction (from a randomly selected sample) among a group of 50 participants. In CONTROL, a payment of 300 Euro was offered to a randomly selected participant from a group of 50 participants. We received between 100 and 150 responses per treatment. Hence, we offered payments to three participants per treatment for a total of 15 payments.[2]

2.3 Approach for data analysis

For the first and second objective, first results are obtained by descriptive statistics, visualizations and nonparametric tests. We apply nonparametric multi-comparison Kruskal-Wallis tests to investigate whether the predictions and the accuracy of different samples of forecasters come from the same underlying distributions and pairwise Wilcoxon rank sum test to assess which forecaster samples differ from each other. That is, we ask whether some farmers' behavior is easier or more difficult to predict.

To study the effect of the incentive mechanisms (the third objective), the prediction accuracy is initially assessed using a Kruskal-Wallis-Test and then used as the dependent variable in regression models. Here, two dimensions have to be considered: a financial incentive could (simultaneously) (a) improve the average prediction accuracy and (b) reduce the heterogeneity of the prediction accuracy (i.e. its variance). To simultaneously consider both dimensions, we apply a distributional regression framework, referred to as Generalized Additive Models for Location, Shape and Scale (GAMLSS). The core idea of GAMLSS, introduced by Rigby and Stasinopoulos (2005), is to not only model the expectation of the dependent variable's distributions, but also its other parameters. For the present case, consider extending the standard linear regression model. Here, a GAMLSS can be applied to not only estimate a linear predictor equation for the mean, but also the variance of the distribution[3]:

$$Y \sim N(\mu, \sigma)$$
$$g_1(\mu) = \eta_1 = X_1\beta_1$$
$$g_2(\sigma) = \eta_2 = X_2\beta_2$$

Here, Y represents a vector of observations of the independent variable, which is assumed to be normally distributed, conditional on the sets of dependent variables X_1 and X_2. $g_1(\mu)$ and $g_2(\sigma)$

[2] To decide on the winner, groups were divided into equal size (i.e., the actual group size was a bit smaller than 50 which is conceptually equivalent to rounding up the expected value of payments). We successfully contacted and exchanged banking details and executed payments with 10 out these 15 respondents. One respondent explicitly declined the payment, and four others did not respond to our attempt to contact them.

[3] Note that GAMLSS is a versatile framework, which allows the incorporation of many different effect types (e.g. semiparametric and spatial effects) and complex distributions (with up to 4 parameters). As these possibilities are not of interest here, we refrain from giving a full introduction to the framework. The interested reader is referred to the canonical references (Rigby and Stasinopoulos, 2005; Stasinopoulos and Rigby, 2007).

are the link functions for the corresponding linear predictor equations. This regression model can be estimated using maximum likelihood-techniques. In the presentation of the results in the next section, clustered standard-errors (at the individual level) are presented to account for potential correlations between individuals' errors.

3 Results

The descriptive statistics of the predictions, per predicted sample and over all samples are presented in Table 4. The table also shows the true means by farmer sample. Based on the first task of Tanaka et al. (2010), farmer can be characterized as slightly risk-seeking on average, with the Polish farmers being the most and the Spanish farmers being the least risk-averse. Note that this characterization serves illustrative purposes, as it changes when structural estimation across all three lottery tasks is taken into account, see the original contribution of Rommel et al. (2022a).

Means range from 4.74 in Spain to 6.30 in Poland, i.e., with a range of 1.64 in the mean, there is a rather large heterogeneity in how farmers respond to the multiple price lists (cf. Rommel et al., 2022a). In contrast, the predictions have a range of only .48 (from 5.58 for Croatia to 6.06 for Poland). Although the predicted means take values over the complete (technically possible) range (from 0 to 12) for all predicted samples, the average predicted mean is close to the true mean in most cases. Pooled for all samples, the difference between the true mean and the predicted mean is .26. The smallest difference is found for the Swedish sample (.01), the largest one for the Spanish sample (1.18). When rounding to integers, which corresponds to values representing choices possible in the MPL, the predicted choice would only differ from the observed average choice for the Spanish, French and Italian sample (by one row). Additional plots of the predictions' distributions of the individual farm systems are presented in Appendix 1.

Table 4: Descriptive statistics of the participants' predictions

	True Mean	Predictions		
Predicted sample		Predicted mean	Median	SD
Sweden	5.70	5.71	6	2.72
Germany	5.71	6.03	6	2.68
Poland	6.30	6.06	6	2.80
Netherlands	5.80	5.94	6	2.74
Spain	4.74	5.92	6	2.74
Italy	4.96	5.80	5.80	2.82
Croatia	6.05	5.58	5.50	2.76
France	5.28	5.89	6	2.62
Pooled predictions	5.61	5.87	5.94	2.01

Notes: Own calculations, true means based on Rommel et al. (2022)

Differentiating the predictions by the predicted samples as well as expert groups conducting the predictions (see box plots in Appendix 2) shows that there are some samples which medians and means of the predictions by expert groups fluctuate around the true mean (e.g. Croatia and Germany), whereas some exhibit a pattern of biased predictions (e.g. Spain and Italy). Nevertheless, when testing for differences between expert groups predictions by farming system, Kruskal-Wallis tests only indicate statistically significant differences between expert groups for the Swedish ($X^2 = 14.08$; $p = 0.050$) and Croatian sample ($X^2 = 22.45$; $p = 0.002$). In more detail, additional pairwise Wilcoxon ranksum tests indicate that the null hypothesis can only be rejected for the expert-group-pair of International Researchers and Polish Farm advisors, in both samples (using the Bonferroni-Holm-correction, at the 5%-level). The predictions can be used to calculate the implied risk aversion coefficients predicted by the experts. While these are not of central interest here, the averages of the implicitly predicted coefficients per sample, together with the ones estimated by Rommel et al. (2022a)'s data for the same task, can be found in Appendix 3 (again, note that these values do not correspond to the ones reported by Rommel et al. (2022a), which are based on all three multiple price lists).

Table 5: Absolute deviations of expert predictions from the true farmers' means

		Predicted farmer samples								
Expert samples	N	Sweden	Germany	Poland	Netherlands	Spain	Italy	Croatia	France	Pooled
Pooled Predictions	561	2.21	2.17	2.26	2.20	**2.41**	2.34	2.25	**2.13**	2.25
Farm Advisors Poland	109	2.59	2.89	2.92	2.60	2.74	2.82	2.66	2.35	**2.70**
International Researchers	76	1.63	1.56	1.88	1.53	2.18	2.08	1.73	1.81	**1.80**
Farm Advisors Croatia	56	2.12	2.09	2.36	2.69	2.52	2.48	2.63	2.22	2.39
Farm Advisors France	72	1.97	1.91	2.11	1.93	1.99	1.90	1.98	1.95	1.97
Farm Advisors Italy	51	2.82	2.46	2.54	2.81	2.60	2.78	2.45	2.05	2.56
Experts Spain	59	2.14	2.19	2.16	2.17	2.41	2.02	2.14	2.08	2.17
Swedish students	69	2.31	2.06	1.98	2.00	2.32	2.28	2.30	2.20	2.18
Other	69	2.09	1.92	1.87	1.93	2.42	2.21	2.08	2.29	2.10

Source: Own calculations, Note: Bold values for highest and lowest absolute deviation across predicted samples and category of experts

Moving beyond the raw predictions, Table 5 displays the prediction accuracy, defined as the deviation from the sample average, by sample and expert group. The last column (*Pooled*) indicates how much the forecaster samples deviate, on average, from the true means across all eight samples. The first row (*Pooled Predictions*) displays how much, on average, all pooled predictions deviate from the true mean for each of the eight samples. In other words, low values in the last column indicate high predictive accuracy of a group of forecasters; low values in the first row indicate that a sample is easier to predict. Note that the sample of researchers provided the most accurate predictions on average, whereas the sample of French farmers was the easiest to predict. The range is smaller when considering the diversity of predicted samples (0.28 – 2.13 for France to 2.41 for Spain) than when considering the diversity of forecasters samples (0.90 – 1.80 for the researchers to 2.70 for the Polish farm advisors). Formal testing reveals that the average accuracy of the predictions per expert group does not come from the same distribution across all samples of predicting experts (Kruskal-Wallis test; $X^2 = 41.01$; $p < 0.001$), indicating that at least two samples of predictors in our data come from a different distribution. Here, pairwise Wilcoxon rank sum tests indicate statistically significant differences between the average predictions of the international researchers and farm advisors from Poland, Croatia and Italy, as well as between the farm advisors from France and Poland as well as Italy (using the Bonferroni-Holm-correction, at the 5%-level).

Table 6 summarizes the distribution of all predictions for the incentive treatments. Overall, the mean accuracies are similar across treatments. A Kruskal-Wallis test ($X^2 = 4.28$; $p = 0.37$) does not reject the null of equal distributions. Differences in the standard deviations are relatively large, and pairwise F-tests reveal at least some incompatibility of the data with the null (e.g., testing the standard deviation of *TOURHIGH* against *CONTROL* yields an F-ratio of 0.63 with p = .017 for the two-sided test). This indicates that incentives may not necessarily lead to different predictions on average, but could help in enhancing the efficiency of predictions (see Camerer and Hogarth (1999) for a discussion on the effect of incentives on the variation of experimental outcomes depending on effort).

Table 6: Average accuracy by incentive treatments

Treatment	N	Minimum	Q1	Q2/Median	Q3	Maximum	Mean	SD
TOURLOW	107	0.52	1.43	1.95	2.77	6.43	2.13	1.12
TOURHIGH	112	0.47	1.36	1.95	2.79	5.46	2.15	1.06
ACCLOW	116	0.64	1.43	1.94	2.67	6.33	2.16	1.10
ACCHIGH	118	0.42	1.52	2.23	3.11	6.43	2.41	1.28
CONTROL	108	0.42	1.39	2.10	3.15	6.37	2.37	1.33

Source: own calculations

After the respondents made their predictions, we implemented a manipulation check on the incentives treatments by asking respondents to correctly identify the incentive scheme they were assigned to. As seen in Appendix 4, between 50% and 70% of the respondents could correctly identify their exact treatment. An additional 15% could at least identify the correct basic incentive mechanism (tournament or accuracy). Since the correct answers were not incentivized, these numbers can be considered large.

Table 7: GAMLSS regressions with accuracy as dependent variable

	Model 1		**Model 2**	
Predictor	μ	σ	μ	σ
Link function	*Linear*	*Log*	*Linear*	*Log*
(Intercept)	2.3729***	0.5651***	2.7176***	0.7802***
	(0.1359)	(0.0458)	(0.3242)	(0.1274)
ACCHIGH	0.0498	-0.0177	0.0081	-0.0626
	(0.1744)	(0.0649)	(0.1847)	(0.0715)
ACCLOW	-0.2025	-0.0788	-0.2622	-0.1420*
	(0.1627)	(0.0641)	(0.1633)	(0.0656)
TOURHIGH	-0.2148	-0.0855	-0.2914+	-0.1455*
	(0.1625)	(0.0600)	(0.1675)	(0.0689)
TOURLOW	-0.2273	-0.1017	-0.1911	-0.1257
	(0.1672)	(0.0718)	(0.1864)	(0.0793)
Overestimation			0.1911*	0.1368***
			(0.0872)	(0.0398)
Expert: International			-0.8337***	-0.3975***
			(0.2122)	(0.1062)
Expert: Farm_Advisors_Croatia			-0.2785	-0.0898
			(0.1970)	(0.0740)
Expert: Farm_Advisors_France			-0.6427***	-0.2429***
			(0.1768)	(0.0648)
Expert: Farm_Advisors_Italy			-0.0215	-0.0191
			(0.1999)	(0.0729)
Expert: Experts_Spain			-0.4085*	-0.1440+
			(0.2001)	(0.0858)
Expert: Swedish_students			-0.5206*	-0.2523***

		(0.2098)	(0.0838)
Expert: Other		-0.4685*	-0.2231***
		(0.2098)	(0.0772)
Female		0.1833+	0.0453
		(0.1020)	(0.0430)
Age		-0.0015	-0.0013
		(0.0049)	(0.0020)
Background Agricultural Sciences/Farming		0.0015	-0.0828
		(0.1342)	(0.0565)
Background Other		-0.1363	-0.0681
		(0.1444)	(0.0664)
Num. Obs.	4,488	4,408	
Pseudo-R^2	0.014	0.087	
AIC	17329.22	16711.22	
Prediction sample FE	Yes	Yes	

Source: own calculations; Notes: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001, Clustered standard errors in parentheses

To further investigate the effects of the financial incentives on the accuracy of predictions, Table 7 presents regression results. As outlined in Section 2.3, distributional regression models are estimated that include linear predictors for both the mean and the variance of the prediction accuracy. The basic specification (Model 1) only includes an intercept, binary controls for the predicted sample (omitted for brevity) and four dummy variables for the five treatments (reference category = *CONTROL*). Model 2 adds the covariates to adjust for the samples of forecasters (reference category: Polish experts; i.e. the largest participant subgroup) and socioeconomic characteristics. In order to account for potential asymmetries in predictions over-, respectively under-estimating farmers' average choices, a binary variable *Overestimation* is included, which takes the value 1 when the prediction underlying the calculated accuracy was above the true mean of the respective sample. All variables are included in both predictor equations. Standard errors are clustered at the individual level to account for correlated predictions within participants. For comparison, analogue estimations for a standard linear model (hence only the distribution's mean, using ordinary least squares estimation) are given in appendix 5.

The regressions show only small and statistically insignificant effects of the treatments on the mean of the prediction accuracy, supporting the results of the previous subsection. The same holds for the effects on the variance of the prediction accuracy. Here, some effects are statistically significant when the model controls for the predictor sample socioeconomic characteristics (Model 2). We also find that accuracy differs by the respondent groups, namely some expert groups (International Researchers, Farm Advisors from France, Swedish students and the miscellaneous group “other”) made more accurate and precise forecasts than the largest participant subgroup (“Polish Advisors”). This supports the findings of the non-parametric tests presented above. Gender, age and professional background showed no statistically significant effects on the prediction accuracy. Finally, the results of the binary variable “*Overestimation”* indicate that predictions were less precise and noisier in cases where a participant predicted a value larger than the true one for a given farmer group.

In order to assess the robustness of the estimates, alternative specifications can be considered. When estimating the models using alternative specifications for the treatment variables (variables indicating the treatment type (accuracy- or tournament- based) and whether an individual was treated or not) or using an alternative distributional assumption for the accuracy (Gamma-distribution) the general findings are confirmed. When analyzing only subsets of the individuals that were able to correctly identify their treatments, respectively treatment types, the same general effect pattern appears (although they are not statistically significant)[4].

The collected data also allows for some exploratory analyses. In the survey, experts were also asked to state their confidence in their predictions on a scale from 0 (not confident at all) to 100 (Very confident). Interestingly, the experts with the most accurate predictions (International researchers and Farm advisors from France) have the lowest average confidence in their predictions (cf. Appendix 6). Figure 1 displays a scatterplot of the average prediction accuracy and the stated confidence in the prediction. The included linear fit suggests that overall, experts with higher confidence tend to provide less accurate predictions (recall that the lower values of the measure indicate higher accuracy.

Finally, it is interesting to understand how important knowledge about the predicted farming systems is. In absence of detailed data about the participants' knowledge about the eight different farming systems, we assume that participants know the farming systems in the

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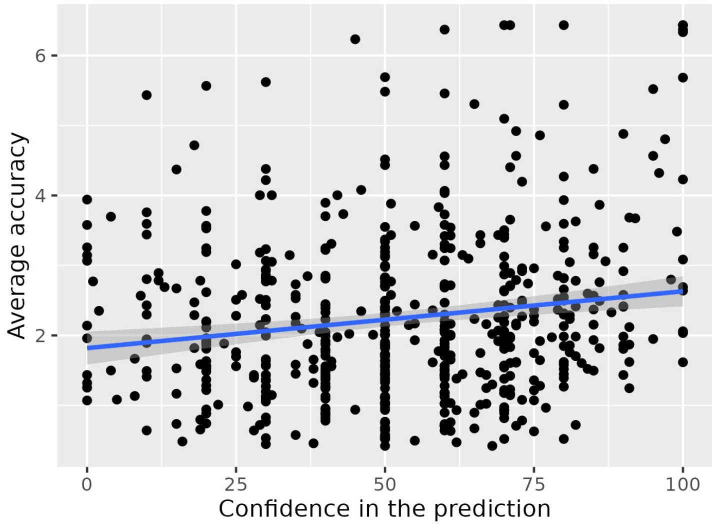
[4] These results can be obtained using the code included in the replication material.

countries they are residing in best. This allows one to create a variable indicating whether a prediction for a given farmer sample was made by an expert from the corresponding country. Considering the subset of participants which are assigned to a country-specific expert group, simple regression analyses (see Appendix 7) indicate that predictions are less accurate when the prediction was made for the participants' country.

Figure 1: Scatterplot of the participants confidence in their predictions and their average prediction accuracy



4 Discussion

The raw predictions of farmers' choices as well as the calculated prediction accuracy exhibits substantial heterogeneity. Yet, averages of predictions are much closer to the actual values reported by Rommel et al. (2022a), supporting the notion of a "wisdom of the crowd effect" (DellaVigna and Pope, 2018b). Here, it is worth noting that the prediction of experts is typically lower then they predict the behavior of farmers from the country they are living in. One potential explanation could be that experts rely on (frugal) heuristics (cf. Gigerenzer and Brighton, 2009) when making predictions for less familiar farming systems but think more about predictions for more familiar settings (and end up making worse predictions compared to relying on a heuristic).

The results on the average prediction accuracy do not indicate significant effects of the monetary incentives on the mean of the accuracy, but suggest that they could lead to less noisy forecasts (i.e. a lower variance of the distribution of the prediction accuracy). The results give some indication that tournament schemes might perform better, but clearly more research is needed here. In this context, one should also investigate whether tournament-based incentives exhibit a gender-heterogeneous treatment effect if compared to accuracy-based incentives on either accuracy or variation (Niederle and Vesterlund, 2007). Given that current research is likely underpowered to identify such effects, future research is required to use the available sample pools in a way that increases the statistical power of this research. The finding regarding accuracy differences between over- and underestimations of the true values suggests that participants that predicted higher levels of risk aversion made less accurate and less noisy predictions. Here it is worth noting that the true mean falls into the risk-seeking domain for the task in most samples, which could drive the differences between over- and underestimations.

One important caveat of the present work has to do with questions around the representativity and the external validity of the results. As often in survey-based experiments, limited possibilities to sample from the whole underlying population, as well as potential self-selection of the respondents limit the external validity of the results. In the present case, this issue is present at two levels: for expert groups making the predictions, but also the samples of farmers whose behavior was predicted. Particularly the second level introduces some nuances relevant for the final interpretation of results. As long as the results of by Rommel et al. (2022a) are interpreted as representative for the underlying population, the present results could be interpreted as holding for the underlying population. If one does not follow this assumption, the interpretation of the results is limited to the specific samples studied by Rommel et al. (2022a). Also, a general critique of multi-price-list elicitation methods concerning the complexity of such tasks (Dave et al., 2010) applies to predictions of their outcomes as well.

It has also to be considered that the information about the groups of farmers (respectively their farming systems) given to the participants is rather coarse, forcing the participants to provide forecasts based on previous knowledge and intuition. Investigating the ability of experts to predict the outcomes of individual farmers or smaller, homogenous groups of farmers could be a fruitful extension of the present research. Also, quantitative data on past behavior of farmer (groups) could be provided to better understand differences between intuition- and data-driven forecasts (Grossmann et al., 2023). We have offered all respondents a short summary of the research results. It would be instructive to see whether or not experts update their beliefs after taking part in a prediction and receiving feedback (Vivalt and Coville, 2022).

Finally, it has to be considered that predictions were only obtained for one experimental risk preference elicitation task. The original study included three multiple price lists to elicit parameters for cumulative prospect theory. Here, we have only used one of the lists to understand risk preferences. Although this has arguably allowed us to substantially simplify the task for respondents and to obtain a larger sample, it comes at the cost of understanding more about other aspects of risk preferences, such as the degree of loss aversion or probability weighting. While one may carry out such investigations in the future, one should likely also consider that this could limit the sample of forecasters. Further investigating how elicitation formats and the complexity of instructions drive response rates and accuracy is, hence, important.

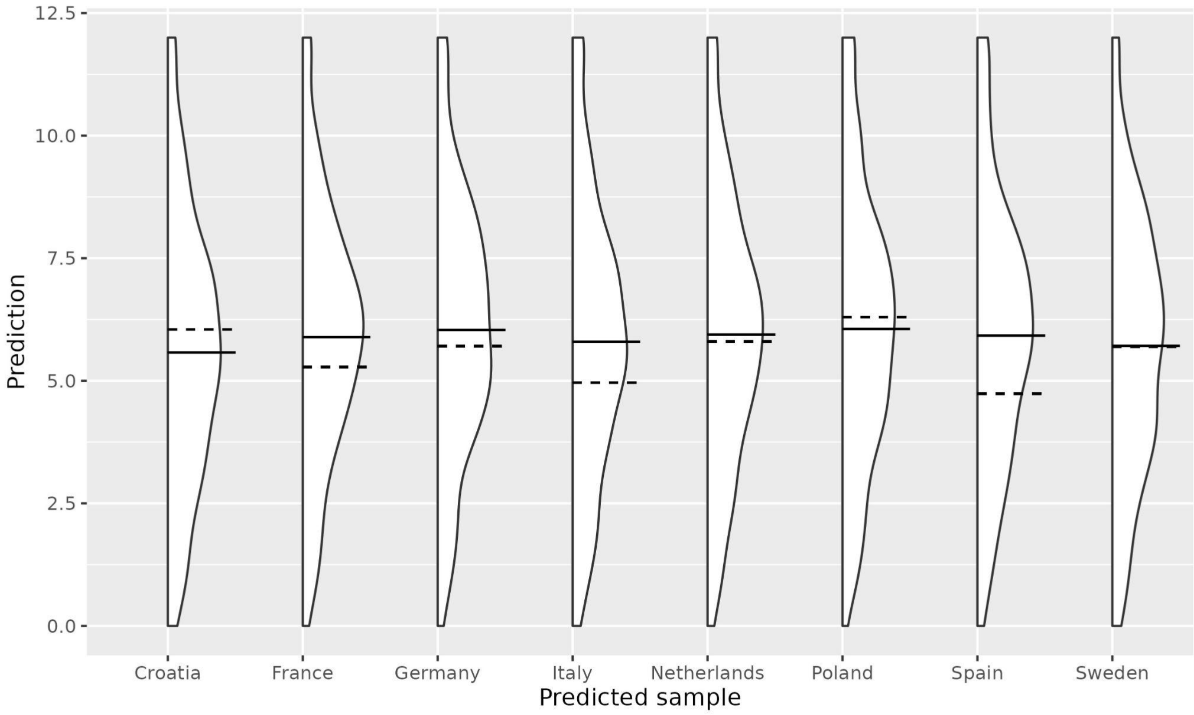
5 Conclusions

There is no in-depth understanding of stakeholder perceptions of farmers' risk preferences. By analyzing the predictions of 561 agricultural experts of farmers’ behavior in a multiple-price-list experiment for the determination of risk preferences for different groups of farmers, this study provided first insights into this previously neglected issue. Building on the recent work by Rommel et al. (2022a), experts had to predict the average outcome of one of MPLs used in the approach introduced by Tanaka et al. (2010) the following farmer groups: wine growers in Croatia, olive farmers in Italy and Spain, potato growers in France as well as arable farmers in the Netherlands, Sweden, and Germany. The predictions were financially incentivized through five different treatment mechanisms (two tournament-based, two accuracy-based and one control treatment with a fixed payment).

Combining the predictions with the actual behavior of the farmers reported by Rommel et al. (2022a) allowed us to study the accuracy of these predictions. With respect to the studies objectives, it can be concluded that there are differences in the prediction accuracy of different farmers groups. Nevertheless, only few differences can be considered to be statistically significant when also taking the different expert groups into account. Interestingly, predictions are less accurate, when experts predict the behavior of farmers from their own country. The results further show that the average prediction accuracy is not affected by the different financial incentive mechanisms, but suggest that they potentially reduce the variability of predictions. By making differences between prior beliefs and the experimental results of Rommel et al. (2022a) visible, the study can enable participants to update their prior beliefs.

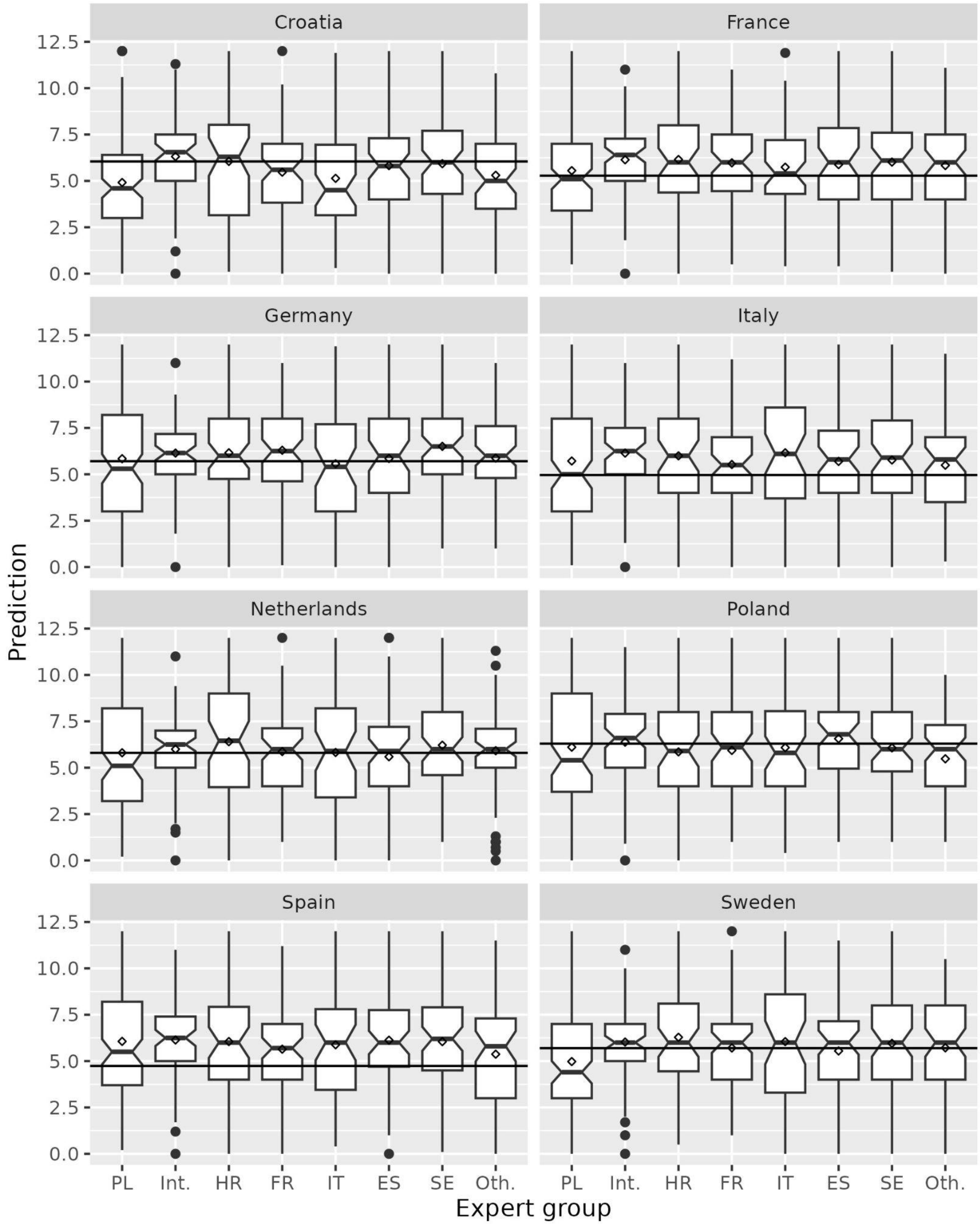
Appendices

Appendix 1: Distributions of the predictions and observed responses of the different farming systems



Notes: Own calculations, solid lines: means of the predictions, dashed lines: means of the observed responses in Rommel et al. (2022)

Appendix 2: Predictions by sample and expert group



Notes: Own calculations, additionally to the boxplot-conventions, diamonds indicate the mean, the notches indicate the approximate 95% - interval of the sample-median. Horizontal lines indicate the true means reported by Rommel at al. (2022).

Appendix 3: R-values implied by the predictions

Country	Average predicted r-value	Observed average r-value
Croatia	1.1956	1.1243
France	1.1553	1.0577
Germany	1.1433	1.1272
Italy	1.1885	1.0981
Netherlands	1.1584	1.1265
Poland	1.1873	1.2343
Spain	1.1643	0.9863
Sweden	1.1626	1.0541

Source: own calculations

Appendix 4: Control question for treatment mechanism

Assigned treatment		Answer ACCHIGH	ACCLOW	CONTROL	TOURHIGH	TOURNLOW	I don't know
ACCHIGH	N	67	19	8	9	2	13
	%	56.8	16.1	6.8	7.6	1.7	11.0
ACCLOW	N	17	68	9	11	1	10
	%	14.7	58.6	7.8	9.5	0.9	8.6
CONTROL	N	4	12	71	16	0	5
	%	3.7	11.1	65.7	14.8	0.0	4.6
TOURHIGH	N	11	20	8	60	0	13
	%	9.8	17.9	7.1	53.6	0.0	11.6
TOURNLOW	N	5	17	10	14	48	13
	%	4.7	15.9	9.3	13.1	44.9	12.1
All	N	104	136	106	110	51	54
	%	18.5	24.2	18.9	19.6	9.1	9.6

Source: own calculations

Appendix 5: Linear regressions with accuracy as dependent variable

	Model 1	Model 2
(Intercept)	2.375***	2.868***
	(0.137)	(0.355)
ACCHIGH	0.046	0.021
	(0.174)	(0.175)
ACCLOW	-0.209	-0.244
	(0.164)	(0.162)
TOURHIGH	-0.218	-0.274+
	(0.162)	(0.160)
TOURLOW	-0.236	-0.222
	(0.169)	(0.167)
Overestimation		0.220*
		(0.086)
Expert: International		-0.907***
		(0.234)
Expert: Farm_Advisors_Croatia		-0.293
		(0.207)
Expert: Farm_Advisors_France		-0.713***
		(0.190)
Expert: Farm_Advisors_Italy		-0.066
		(0.208)
Expert: Experts_Spain		-0.426*
		(0.206)
Expert: Swedish_students		-0.592**
		(0.229)
Expert: Other		-0.600**
		(0.224)
Female		0.161
		(0.106)
Age		-0.004
		(0.005)
Background Agricultural Sciences/Farming		-0.008

		(0.143)
Background Other		-0.135
		(0.153)
Num. Obs.	4488	4408
R2	0.008	0.047
AIC	17335.5	16854.8
Prediction sample FE	Yes	Yes

Source: own calculations; Notes: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001, Clustered standard errors in parentheses

Appendix 6: Confidence in predictions by expert group

Expert samples	Minimum	Median	Mean	SD	Maximum
Farm advisors_Poland	0.00	60.00	60.16	21.70	100.00
International	0.00	40.00	42.28	20.84	90.00
Farm Advisors_Croatia	12.00	70.00	64.93	17.36	99.00
Farm Advisors_France	1.00	40.00	41.04	20.52	81.00
Farm Advisors_Italy	0.00	66.00	60.98	27.06	100.00
Farm Advisors_Spain	0.00	52.00	50.88	22.02	91.00
Swedish students	0.00	50.00	50.81	25.23	100.00
Other	0.00	58.00	51.54	25.36	100.00

Note: Confidence on a scale from 0 (not confident at all) to 100 (very confident)

Appendix 7: Additional regressions with accuracy as dependent variable

	Model 1	Model 2	Model 3
(Intercept)	2.327***	2.350***	2.546***
	(0.032)	(0.086)	(0.473)
Dummy: Own Country	0.194*	0.206*	0.206**
	(0.091)	(0.094)	(0.072)
Controls			
Dummies indicating the predicted sample	No	Yes	Yes
Participant-Dummies	No	No	Yes
N.	3328	3328	3328
R2	0.001	0.004	0.489
R2 Adj.	0.001	0.001	0.414

Notes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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