A test of the gambler's and hot hand fallacies in farmers' weather and market predictions

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Introduction

Uncertainty is prevalent in agricultural production. Much of what determines productivity and farm profit are unknown to farmers when they make decisions for the upcoming growing season. Weather conditions have a significant impact on the year's production level, and resulting farm revenue, but are unknown at the time of planting. Market conditions, including output and some input prices, are also uncertain when many farm decisions are made.

Tools are available to farmers to mitigate some uncertainty, including crop insurance, investment in certain technologies, and forward contracts, but farmers' production and income are still subject to variations in weather and market conditions. When planning their farm activities, farmers must make predictions about the weather and market conditions that will prevail. They must make planting decisions for the coming year, decide how to use their land, and make crop insurance decisions based on information available to them and their predictions about future revenue outcomes. Decisions must be made before these outcomes are known.

Learning about how farmers think about and predict uncertain events is important in understanding how they make economic decisions on their farms. Despite being aware of the likely growing and market conditions for the coming year, farmers may believe that after a string several good or bad years, that the other is 'due.' That is, they may believe that a small sample of years should be representative of the long-term weather and market patterns. Similarly, they may believe that if a gamble has paid off in the past, future gambles are more likely to pay off.

If farmers have information about the likelihood of a certain event occurring, their predictions should not be shaped by past outcomes of that event. If, for example, they know that a drought is likely to occur ten percent of the time, they should not predict that the coming year will bring a drought with certainty even if the past nine years were drought-free. However, research has shown that people do not always make predictions according to objective probabilities and information available to them. That is, people do not always behave rationally.

Two behaviours that describe deviations from rational predictions have been dubbed the hot hand and gambler's fallacies (Rabin and Vayanos, 2010). The gambler's fallacy is characterized by negative recency (Ayton and Fischer, 2004). It is the belief that a small sequence of random outcomes should represent the underlying probabilities that generate the random outcomes. People may believe that a small number of realizations of random events should be representative of the underlying probabilities that generate each outcome, rather than believing that each event will be determined by an underlying probability.

This behaviour is often called belief in the law of small numbers (Tversky and Kahneman, 1971; Rabin, 2002). Agents may expect outcomes of a random process to be representative of the long-term probabilities used to generate outcomes, rather than believing each outcome to be an independent event. For example, after a sequence of three heads in a fair coin toss, people who behave according to the gambler's fallacy believe that tails is more likely than heads in the next toss, since tails is 'due' (even though the two events are independent and the probability of either occurring is 0.5).

The hot hand fallacy also stems from a misinterpretation of objective probabilities. It is the belief that, if a person correctly performs a task or predicts the outcome of a certain random event, that person is on a winning streak and therefore has the "hot hand" (Ayton and Fischer, 2004). It is also referred to as positive recency, in that the outcome of an event will be the same as the previous one. The hot hand fallacy is different from the gambler's fallacy in that is not a belief about the outcomes *per se*, but a belief about the person's performance (Ayton and Fischer, 2004; Croson and Sundali, 2005; Guryan and Kearney, 2008).

These concepts have been studied in several contexts. Research has been conducted on subjects in a lab setting, finding evidence of both the gambler's and hot hand fallacies. Ayton and Fischer (2004) conducted experiments with undergraduate students, asking them to predict or bet on the outcome of a computerized roulette wheel, finding evidence of the gambler's fallacy among students who predicted the outcome and evidence of the hot hand fallacy among those who placed bets.

Evidence of the gambler's fallacy has also been found in people's real world decisions. Clotfelter and Cook (1993) and Terrell (1994) found that lottery numbers were less likely to be played after being drawn (an effect that lasted several weeks). Croson and Sundali (2005) examined gambling decisions in casinos. Using video of roulette wheels to observe betting after streaks of a particular colour or number, they looked for behaviour consistent with the gambler's and hot hand fallacies. They found that people were less likely to bet on an outcome after it occurred several times (e.g., after a streak of six red outcomes, people were more likely to bet on black than after a streak of two red outcomes), consistent with the gambler's fallacy.

Chen, Moskowitz, and Shue (2016) applied the concept of the gambler's fallacy to baseball umpires, asylum court judges, and loan applications. Using observational data on calls made by baseball umpires and judges' case decisions, they found evidence of the gambler's fallacy. Controlling for pitch and game characteristics, umpires were found to be less likely to call a strike if a strike had been called on the previous pitch. Similarly, judges were less likely to grant asylum in a particular case if they had granted asylum in their previous cases, even when the authors controlled for judge and case characteristics. In the same paper, loan officers participating in hypothetical loan approval experiments using existing loan applications were less likely to approve a loan if they had approved the previous application. This result held regardless of the compensation structure (i.e., whether loan officers were paid a flat rate or per correct approval), although the authors found that loan officers were less likely to behave according to the gambler's fallacy when they were rewarded for correct approval decisions. In all three cases (umpires, judges, and loan officers), less experienced individuals were more likely to exhibit this behaviour.

Support for the hot hand fallacy has also been found outside the laboratory. Gilovich, Vallone, and Tversky (1985) found that basketball spectators and players were more likely to predict a successful shot when the previous shot had been successful, despite evidence to the contrary. Potentially contradicting the findings of Clotfelter and Cook (1993) and Terrell (1994), Guryan and Kearney (2008) found that lottery ticket sales increased in stores that had previously sold a winning ticket.

To our knowledge, these concepts have not been studied among farmers in the context of supply-side decisions. List and Haigh (2009) demonstrated the importance of studying behaviours among a population of interest rather than extrapolating results from the general population (or, in their case, the population of undergraduate students). They show that investment professionals behave differently from students with less investment experience, and that professionals' behaviour is more consistent with rational expectations rather than behavioural anomalies (List and Haigh, 2009).

These behaviours are important to understand in an agricultural production context, as they may impact how producers make decisions on their farms. If farmers believe that they are due a turnaround in crop production conditions, in accordance with the gambler's fallacy, then they may not make best use of information available. Conversely, if they make a gamble that pays off, they may be more likely to make similar gambles in their future decisions, consistent with the hot hand fallacy. In both cases, resources may not be allocated in ways that best meet the farmers' objectives.

This work looks for evidence of the gambler's and hot hand fallacies among farmers, examining how they make predictions and decisions based on previous outcomes and the objective information available to them. Using predictions made by farmers in hypothetical scenarios, we examine whether and how farmers' weather predictions deviate from the objective probabilities given to farmers to test for evidence of the gambler's fallacy. We also use predictions and decisions in hypothetical crop insurance scenarios to look for evidence of the hot hand fallacy.

Conceptual framework

Gambler's fallacy

Formally, the gambler's fallacy can be represented by the following theoretical framework. When a sequence of successive outcomes is independently drawn, a person with casual knowledge of statistics may confound the expectation across the sequence with a conditional expectation. Consider three independent events x_t, $t \in \{1,2,3\}$, where the probability of each is $p(x_i = U) = \pi \in (0,1)$ and $p(x_i = D) = 1 - \pi$. The ex-ante probability of outcome $\{x_1 = U, x_2 = U, x_3 = U\}$ is $p(U,U,U) = \pi^3$ whereas the time $t = 2$ probability of U at time $t = 3$ is π, regardless of prior outcomes. Thus, the probability that $x_3 = U$ given that the prior two outcomes were U is $p(U \mid U,U) = \pi$, which is larger than $p(U,U,U) = \pi^3$. The casual observer may mistakenly believe that, as the ex-ante probability of three Us is smaller than $p(U \mid U,U) = \pi$, independence requires that $x_3 = D$ in order to bring the average closer to the ex-ante expectation (Clotfelter and Cook, 1993; Terrell, 1994). If he holds this belief, he will be more likely to assign a higher probability to the outcome $x_3 = D$ than the objective probability of that event occurring.

Rabin (2002) makes the analogy of independent draws from an urn; someone who behaves according to the gambler's fallacy (the law of small numbers) predicts outcomes as if the sequence is being generated by drawing out of an urn without replacement. For a sequence of length N, the agent believes that πN draws will be U, and $(1-\pi)N$ draws will be D, where πN and $(1-\pi)N$ are integers. Thus, after n outcomes have been observed, the agent's beliefs about the probabilities update to $(\pi N - U_n)/(N-n)$ and $[(1-\pi)N - D_n]/(N-n)$, where U_n and D_n are the number of U and D outcomes observed in the n realizations (Rabin, 2002).

Hot hand fallacy

A similar framework can be used to represent the hot hand fallacy. The hot hand fallacy is a belief that, after correctly predicting a random outcome, a person has the "hot hand" and will continue to prediction correctly. Rather than a belief about the random event itself, as with the gambler's fallacy, the hot hand fallacy is a belief about the person predicting the outcome(s).

Again, consider three independent events x_t, $t \in \{1,2,3\}$, where $p(x_i = U) = \pi \in (0,1)$ and $p(x_i = D) = 1-\pi$. The ex-ante probability of outcome $\{x_1 = U, x_2 = U, x_3 = U\}$ is $p(U,U,U) = \pi^3$ whereas the time $t = 2$ probability of U at time $t = 3$ is π regardless of prior outcomes. If an agent correctly predicts two successive U outcomes, she may believe that she is on a winning streak and predict $x_3 = U$, regardless of the objective probability of another U occurring. Thus, successive correct predictions may make people more likely to predict a certain outcome than the objective probability that the outcome will occur.

Data

Our data come from two surveys of farmers. The first was conducted among farmers in the Prairie Pothole Region of North and South Dakota in March 2016. Four focus group meetings were convened with farmers (three in East Central South Dakota and one in East Central North Dakota, all along the James River). This region was chosen due to the high rate of conversion of grassland to grow row crops. At these meetings, farmers completed surveys about their actual land use decisions and reported willingness to pay for land conversion in hypothetical land use scenarios.

Participants also made land use decisions in hypothetical scenarios, deciding whether or not to convert land from grass to crop land. Farmers were provided with information about returns to land under both uses, the conditional probability of a good or bad year occurring (the probability of a good/bad year following a good/bad year), and an annual per-acre conversion cost. The outcome generation process conformed with the Markov property, i.e., only the current state matters when forming expectations.

Participants were asked to make a prediction about the coming year's weather and market conditions and to decide whether to put their land in grass or crop. After these decisions were made and recorded[1], weather and market conditions were revealed to participants. Each year's revenue was determined by the farmer's land use decision as well as the random weather and market conditions for that year. Decisions were then made for the next year. Two to four rounds of ten years each were played with participants. The returns to land, the probabilities of good/bad years, and annual conversion costs were varied across different rounds.

Farmers' total compensation for attending the two-hour meeting was based on their land

[1] Predictions, decisions, and outcomes were recorded on a single sheet of paper for each round, so that farmers were aware of all previous predictions and outcomes.

use decisions and the weather/market conditions in this module of the survey. Farmers were compensated a proportion of their total income in one of the rounds chosen at random. Their total compensation ranged from $50 to $80.

The second survey was conducted with corn and soybean farmers in Michigan and Iowa in early 2017 and focused on farmers' crop insurance choices. The final section of the survey presented hypothetical corn growing scenarios, completed by farmers in person or online. Participants were shown two potential revenue outcomes, which depended on weather and market conditions for that year. Farmers had the option of purchasing insurance, the cost of which was the same every year in that round. At the beginning of each year, farmers were asked to make predictions[2] about the coming year's weather and market conditions, and decide whether or not to purchase insurance. Predictions and insurance decisions were recorded on a decision sheet for that round.[3] They then rolled a single die, which determined whether their growing season was good or bad. If a one through five was rolled, the conditions for that year were good. If a six was rolled, the conditions were bad.[4] Farmers' revenue for that year was recorded, and predictions and decisions were made for the next year. This continued for seven years; another seven-year round was played in which the revenue outcomes and insurance premium were changed.

Participants were paid a base rate for completing the survey, plus a portion of their revenue outcome for a year in a particular round of the final section. The round and year were both chosen at random. Compensation was based on a particular year, rather than their total

[2] In this survey, farmers were given the option of saying they were unsure about the coming year's prediction, rather than only being able to predict good and bad years. In this analysis, only good and bad predictions are considered.
[3] In the online version, the cumulative predictions, decisions, and outcomes were shown to participants prior to making a prediction for the coming year.
[4] Weather and market outcomes in the online survey were determined by a random number generator, choosing an integer from 1 to 6. To simulate rolling a die, if the number was between one and five, the condition was good. If the number was a six, the condition was bad. Each number had an equal probability of being generated.

revenue for a particular round, to minimize the potential effect of accumulated revenue.

Empirical Methods

Gambler's fallacy

To test for evidence of farmers behaving according to the gambler's fallacy, we constructed variables to indicate whether a string of good or bad years had occurred (i.e. indicator variables for two continuous good years, three continuous good years, etc.). Similar indicator variables were constructed for strings of bad years.

Using data from both surveys, we looked for evidence of the gambler's fallacy by estimating of the probability that a particular condition (good or bad) was predicted after a streak of length n, $n \in \{1, \ldots, 5\}$. The linear regression equation for the probability of predicting a good outcome is shown in (1) below

$$p(good_{i,t}) = \beta_0 + \beta_1 good\_n_{i,t} + \beta_2 p(good) + \beta_3 year_{i,t} + \sum_{j=n-m}^{n} \gamma_j good\_lag_j + \mu_i + \varepsilon_{i,t} \quad (1)$$

where $good_{i,t}$ indicates that a participant i predicted that year t would be good, $good\_n$ is an indicator variable taking on the value 1 when the previous n outcomes were good and 0 otherwise, $p(good)$ is the probability that a good year will follow a good year, and $year$ is a dummy variable to control for and year. Unobserved heterogeneity is represented by μ_i, and $\varepsilon_{i,t}$ is a normally distributed error term. Indicator variables for lags of good years are also included, represented in (1) by $good\_lag_j$, so that the impact of a run of good outcomes is captured by β_1. A similar equation was used to estimate the probability of a "bad" prediction following a string of bad years of length n, $n \in \{1, \ldots, 5\}$. For both, random effects probit regressions were run.

In these scenarios, a good (bad) year was always more likely to follow a good (bad) year; farmers should therefore be more likely to predict a good (bad) year when the previous year was good (bad). Runs of the same outcome should have no additional impact on a farmer's prediction. Participants were shown the probability that a particular outcome would follow the present outcome, which varied by round, and we hypothesize that farmers' predictions of good years will be higher for higher probabilities. These hypotheses can be stated by the following.

$$H_1 : \beta_1 < 0,\ n \in \{1, \dots, 5\}$$
$$H_2 : \beta_2 > 0$$

Using data from the second survey we can estimate a similar linear equation. However, due to the nature of the probabilities of good and bad outcomes, our hypotheses differ slightly. The probabilities of good and bad years were determined by the roll of a single six-sided die. The probability of a good year was 5/6 and that of a bad year was 1/6; these probabilities did not change with the previous outcome or with versions and rounds. Participants should therefore have always predicted a good year in time t regardless of the conditions in year $t-1$. The regression equation for this dataset is

$$p(good_{i,t}) = \alpha_0 + a_1 good\_n_{i,t} + \alpha_2 year_{i,t} + \sum_{j=n-m}^{n} \delta_j good\_lag_j + \mu_i + \varepsilon_{i,t} \tag{2}$$

where variables are as described above.

Our hypothesis for these data can be stated as

$$H_1 : \alpha_{1_n} < 0,\ n \in \{1, \dots, 5\}$$

Hot hand fallacy

To test for the hot hand fallacy, we use data from the crop insurance survey only. We treat farmers' insurance decisions as bets; if they decide not to purchase crop insurance, we say that they are "betting" that the coming year will be good.

To look for evidence of the hot hand fallacy, we estimate the effect of previous successful bets on the probability that a farmer will purchase insurance for the coming year. We test the effect of sequential successful bets of length $n,\ n \in \{1,2,3\}$. The main equation to be estimated is

$$p(insurance_{i,t}) = \theta_0 + \theta_1 success\_n_{it} + \theta_2 average\_insurance_i + \mu_i + \varepsilon_{i,t} \qquad (3)$$

where $insurance_{i,t}$ is an indicator variable with the value 1 if farmer i purchases insurance in year t, and $success\_n_{i,t}$ indicates whether the previous n bets were successful. To control for a farmer's propensity to purchase insurance we include the proportion of insurance purchases in the opposite round[5], $average\_insurance_i$. Our main coefficient of interest is θ_1. We hypothesize that $\theta_1 < 0$ if farmers behave according to the hot hand fallacy. That is, we hypothesize that successful bets will result in farmers being less likely to purchase insurance, and therefore more likely to gamble, in the coming period.

Other estimations were run to include the average insurance purchases, as well as year and round indicator variables. As with estimations to test for the gambler's fallacy, probit regressions were run to test for the hot hand fallacy.

<u>*Results*</u>

Gambler's Fallacy

Summary predictions

Data from two surveys were combined for this analysis. Seventy-six farmers completed the first survey at focus group meetings in North and South Dakota. The second survey was completed in person and online by farmers in Michigan and Iowa. To date, data from 141 of

[5] Opposite round indicates the round for which insurance purchases are not being examined, i.e. round 2 if insurance purchases in round 1 is the dependent variable, and vice versa.

these surveys have been compiled.

Participants who attended meetings in North and South Dakota completed two to four rounds of hypothetical land conversion scenarios, making ten weather predictions in each round. Due to the potential for learning effects, the first round has been excluded from this analysis, leaving a total of 1,474 prediction observations.

For the crop insurance scenarios in the second survey, two rounds of seven years each were completed by participants, for a total of 1,974 prediction observations.

The total number of good predictions after one to five consecutive good years from the first and surveys, are shown in Tables 1 and 2, respectively. Data from the land conversion survey show that fewer participants predict a good year as the number of consecutive good years increases, providing some evidence of the gambler's fallacy. A similar pattern is not observed in data from the crop insurance survey; the proportion of good predictions remains roughly constant after successive numbers of good outcomes.

Similar patterns in bad year predictions were observed, as shown in Tables 3 and 4. In predictions from the land conversion scenarios, the proportion of bad years predicted decreases as the number of consecutive bad years increases, suggesting that participants did not base their predictions solely on the information presented to them. Data from the crop insurance scenarios show a similar pattern. However, few strings of bad outcomes were observed, resulting in a small number of observations.

Regression results

Regression results for the probabilities of predicting good years are presented in Tables 5 and 6 below. We do not find support for the gambler's fallacy in farmers' weather predictions in either dataset.

In the first survey, farmers were more likely to predict a good year after successive good years had occurred. As shown in Table 5, the only variable with a significant impact on farmers' predictions was the probability of a good year occurring; past year's weather outcomes had no effect. Farmers were told that, after a good outcome, the next year was more likely to be good than bad.

In the second survey, no impact of previous outcomes was found on farmers' predictions. As shown in Table 6, consecutive good outcomes of any length were not found to have a significant impact on the probability that farmers predicted a good outcome in the following year, contradicting our stated hypothesis.

These general results hold when the data are restricted to farmers who changed their predictions from year to year, a total of 47 participants (see Table 8). One participant consistently predicted bad years, 26 predicted only good years, and 20 refused to make a prediction. Regressions were also run in which variables were included to control for the average number of good years predicted in the opposite round, yielding similar results (see Table 9).

Hot Hand Fallacy

We examined the data for behaviour consistent with the hot hand fallacy by treating farmers' insurance purchasing decisions as bets about their predictions, measuring the impact of successful bets on insurance purchases for the coming year. Participants who always or never purchased insurance were excluded from this analysis (69 and 9 participants, respectively).

We find that farmers were less likely to purchase insurance if the previous year's bet had been successful. We found no impact of having two or more successive successful bets (see Table 7). Interestingly, the coefficient on the second lagged successful bet is positive, indicating that farmers are more likely to purchase insurance if they bet successfully the second to last year. These results hold after controlling for average insurance purchases (the proportion of years in which insurance was purchased) as well as round and year effects.

This provides evidence that farmers behave according to the hot hand fallacy. After a successful bet, farmers are more likely to bet for the coming growing season by not purchasing insurance. This is despite the fact that probabilities of either state occurring did not change from year to year in these hypothetical scenarios.

Discussion

The results from our hypothetical land use and crop insurance scenarios provide evidence that farmers do not behave according to the gambler's fallacy, but exhibit behaviour consistent with the hot hand fallacy.

In both hypothetical scenarios, previous outcomes have no impact on farmers' predictions about conditions for the coming year. That farmers' predictions are inconsistent with the gamble's fallacy may reflect the importance of their predictions and resulting decisions on their farm income. While Chen et al (2016) did find evidence of the gambler's fallacy among loan officers' approval decisions, the effects of previous decisions were not statistically significant when the loan officers were compensated according to their success rate. This suggests that when incentives are such that agent's decisions determine compensation, they are less likely to behave according to the gambler's fallacy. These results are consistent with List and Haigh (2010), who found that professional traders were more likely to behave rationally than undergraduate students.

While these decisions were made for stylized hypothetical scenarios, farmers make similar predictions and insurance decisions every year. When evidence of the gambler's fallacy was found in real world decisions, these decisions did not have a direct impact on agents' income. While money may be on the line, gambling at casinos may be viewed as entertainment rather than a source of income, causing agents to make irrational predictions and behave according to the gambler's fallacy as found by Croson and Sundali (2005).

The fact that farmers' yearly revenue directly depends on the predictions and decisions they make every year may cause them to pay closer attention to the information available to them and to use that information more rationally than those gambling at a casino or participants in an economic study. This may be the reason that the gambler's fallacy is observed in some scenarios but not among the decisions made by farmers, even in our hypothetical scenarios.

Despite no evidence of the gambler's fallacy, farmers' insurance purchases indicate that they may behave according to the hot hand fallacy. Rather than a belief about the underlying process generating outcomes, the hot hand fallacy is a belief about the person making predictions or gambles about these outcomes. If a farmer predicts correctly, he may believe he is on a winning streak, or has the hot hand, and continue to gamble in the future. In these hypothetical scenarios, if farmers did not purchase insurance in the previous year, thus "betting" that the year would be good, and the bet was successful, they were less likely to purchase insurance for the coming year.

Learning directly from farmers how they make predictions about future revenue conditions can help understand how they make important production decisions, such as land conversion and crop insurance. These results have implications for how farmers plan and make predictions for future growing seasons. Farmers must make many production decisions in advance, and have many tools available to them to manage risk and uncertainty. How their predictions are formed may determine resource allocation and risk mitigation strategies.

Tables and Figures

Table 1. Proportion of good weather predictions for after a run of 1 to 5 good weather outcomes (land conversion survey)

Consecutive good weather outcomes	Proportion of good predictions	Observations
1	0.687	846
2	0.684	602
3	0.671	431
4	0.680	306
5	0.630	230

Table 2. Proportion of good weather predictions for after a run of 1 to 5 good weather outcomes (crop insurance survey)

Consecutive good weather outcomes	Proportion of good predictions	Observations
1	0.841	779
2	0.839	522
3	0.834	350
4	0.850	214
5	0.857	119

Table 3. Proportion of bad weather predictions after a run of 1 to 5 bad weather outcomes (land conversion survey)

Consecutive bad weather outcomes	Proportion of bad predictions	Observations
1	0.384	563
2	0.356	320
3	0.361	191
4	0.374	123
5	0.329	73

Table 4. Proportion of bad weather predictions after a run of 1 to 3 bad weather outcomes (crop insurance survey)

Consecutive bad weather outcomes	Proportion of bad weather predictions	Observations
1	0.148	187
2	0.056	36
3	0.000	4

Table 5. Probit regression results (random effects, marginal effects reported) of predicting a good year after *n* sequential good outcomes (land conversion survey)

n	1	2	3	4	5
Consecutive good outcomes of length *n*	0.046*	0.058	0.047	0.025	-0.085
	(0.026)	(0.062)	(0.054)	(0.056)	(0.062)
p(good year)	0.322 ***	0.320***	0.282**	0.349***	0.495***
	(0.101)	(0.112)	(0.117)	(0.125)	(0.138)
Number of observations	1409	1141	1007	873	739
Number of individuals	65	65	65	65	65
R^2	0.048	0.057	0.057	0.066	0.079

Table 6. Probit regression results (random effects, marginal effects reported) of predicting a good year after *n* sequential good outcomes (crop insurance survey)

n	1	2	3	4	5
Consecutive good outcomes of length *n*	-0.0137	0.0991	-0.00576	0.0591	0.0401
	(0.0190)	(0.0755)	(0.0473)	(0.0585)	(0.0629)
Observations	966	797	636	470	306
Number of participants	119	116	115	113	106

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7. Probit regression results of purchasing insurance after 1 or 2 successful “bets” (crop insurance survey, participants who did not change insurance purchases excluded)

n	1	1	1	2	2	2
Successful bet in period $t-1$	-0.136***	-0.130***	-0.133***	-0.104*	-0.0985*	-0.101*
	(0.0418)	(0.0416)	(0.0420)	(0.0563)	(0.0555)	(0.0562)
Successful bet in period $t-2$				0.147***	0.153***	0.153***
				(0.0523)	(0.0517)	(0.0525)
Two successive successful bets				-0.0586	-0.0670	-0.0680
				(0.0774)	(0.0765)	(0.0774)
Average insurance purchases, opposite round	-0.831***	-0.835***	-0.818***	-0.899***	-0.901***	-0.886***
	(0.0789)	(0.0776)	(0.0830)	(0.0714)	(0.0705)	(0.0772)
Observations	708	708	708	590	590	590
Controls						
Year	No	Yes	Yes	No	Yes	Yes
Round	No	No	Yes	No	No	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Additional tables

Table 8. Probability of predicting a good year after a string of n good years, after a string of good year of length n (probit random effects regression, marginal effects reported)

n	1	2	3	4	5
Consecutive good outcomes of length n	-0.0137	0.0991	-0.00576	0.0591	0.0401
	(0.0190)	(0.0755)	(0.0473)	(0.0585)	(0.0629)
Observations	966	797	636	470	306

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9. Probability of predicting a good year after a string of n good years, restricted to participants who changed their predictions (probit random effects regression, marginal effects reported)

n	1	2	3	4	5
Consecutive good outcomes of length n	-0.0346	0.194	-0.00518	0.0986	0.0830
	(0.0405)	(0.139)	(0.0950)	(0.101)	(0.117)
Observations	642	527	420	308	198

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10. Probability of predicting a good year after a string of *n* good years, restricted to participants who changed their predictions, controlling for average number of good predictions (probit random effects regression, marginal effects reported)

n	1	2	3	4	5
Consecutive good outcomes of length *n*	-0.0140	0.124	-0.0418	0.0798	0.0663
	(0.0320)	(0.131)	(0.0783)	(0.0874)	(0.100)
Mean number of good predictions in the opposite round	-0.406**	-0.406**	-0.326**	0.312***	0.303***
	(0.172)	(0.169)	(0.157)	(0.0654)	(0.0804)
Observations	633	519	414	302	194

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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