1-1-2015

Making Detailed Predictions Makes (Some) Predictions Worse

Theresa Kelly
University of Pennsylvania, theresa.f.kelly@gmail.com

Making Detailed Predictions Makes (Some) Predictions Worse

Abstract
In this paper, we investigate whether making detailed predictions about an event makes other predictions worse. Across 19 experiments, 10,895 participants, and 415,960 predictions about 724 professional sports games, we find that people who made detailed predictions about sporting events (e.g., how many hits each baseball team would get) made worse predictions about more general outcomes (e.g., which team would win). We rule out that this effect is caused by inattention or fatigue, thinking too hard, or a differential reliance on holistic information about the teams. Instead, we find that thinking about game-relevant details before predicting winning teams causes people to give less weight to predictive information, presumably because predicting details makes information that is relatively useless for predicting the winning team more readily accessible in memory and therefore incorporated into forecasts. Furthermore, we show that this differential use of information can be used to predict what kinds of games will and will not be susceptible to the negative effect of making detailed predictions.

Degree Type
Dissertation

Degree Name
Doctor of Philosophy (PhD)

Graduate Group
Operations & Information Management

First Advisor
Joseph P. Simmons

Keywords
decision-making, forecasting

Subject Categories
Other Psychology | Psychology | Social and Behavioral Sciences

MAKING DETAILED PREDICTIONS MAKES (SOME) PREDICTIONS WORSE

Theresa F. Kelly

A DISSERTATION

in

Operations and Information Management

For the Graduate Group in Managerial Science and Applied Economics

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

2015

Supervisor of Dissertation

____

Joseph P. Simmons, Associate Professor of Operations and Information Management

Graduate Group Chairperson

____

Eric Bradlow, The K.P. Chao Professor of Marketing, Statistics, and Education

Dissertation Committee

Uri Simonsohn, Associate Professor of Operations and Information Management

Deborah Small, Associate Professor of Marketing and Psychology

Gal Zauberman, Laura and John J. Pomerantz Professor of Marketing and Psychology

ABSTRACT

MAKING DETAILED PREDICTIONS MAKES (SOME) PREDICTIONS WORSE

Theresa F. Kelly

Joseph P. Simmons

In this paper, we investigate whether making detailed predictions about an event makes other predictions worse. Across 19 experiments, 10,895 participants, and 415,960 predictions about 724 professional sports games, we find that people who made detailed predictions about sporting events (e.g., how many hits each baseball team would get) made worse predictions about more general outcomes (e.g., which team would win). We rule out that this effect is caused by inattention or fatigue, thinking too hard, or a differential reliance on holistic information about the teams. Instead, we find that thinking about game-relevant details before predicting winning teams causes people to give less weight to predictive information, presumably because predicting details makes information that is relatively useless for predicting the winning team more readily accessible in memory and therefore incorporated into forecasts. Furthermore, we show that this differential use of information can be used to predict what kinds of games will and will not be susceptible to the negative effect of making detailed predictions.

TABLE OF CONTENTS

ABSTRACT ii
TABLE OF CONTENTS iii
LIST OF TABLES vi
Tables in the main text vi
Tables in Appendix A1: Experimental instructions and designs vi
Tables in Appendix A2: Additional measures vii
Tables in Appendix A3: Alternative analyses ix
LIST OF FIGURES xii
Figures in the main text xii
Figures in Appendix A1: Experimental instructions and designs xii
Figures in Appendix A2: Additional measures xviii
INTRODUCTION 1
Prior research on detailed predictions 1
Forecasters only consider a subset of relevant information 4
Forecasters use the information that is most accessible in memory 7
Forecasters do not weigh information properly 10
The present research: How do detailed predictions affect prediction quality? 12
GENERAL METHODS 15
Sample 16
Procedure 16
Prediction Quality 22
Additional Measures 23
RESULTS 27
Does predicting scores make winner predictions worse? 27
Does predicting other event details make predictions worse? 29
Are predictions worse because people pay less attention? 31
Are predictions worse because people think harder? 34
Are predictions worse because people think less globally or more locally? 37
Do people who make detailed predictions use useful information less? 38
Which games will show the effect? 44

GENERAL DISCUSSION 47
APPENDIX A1: EXPERIMENTAL INSTRUCTION AND DESIGNS 51
Example Experiment 51
Individual Experiments 59
Experiment 1 60
Experiment 2 63
Experiment 3 67
Experiment 4 71
Experiment 5 75
Experiment 6 79
Experiment 7 82
Experiment 8 85
Experiment 9 89
Experiment 10 90
Experiment 11 90
Experiment 12 91
Experiment 13 94
Experiment 14 99
Experiment 15 100
Experiment 16 105
Experiment 17 111
Experiment 18 115
Experiment 19 116
Excluded Experiments 120
Experiment E1 121
Experiment E2 124
Experiment E3 124
Experiment E4 125
Experiment E5 130
Experiment E6 133
Experiment E7 139
Experiment E8 143

APPENDIX A2: ADDITIONAL MEASURES 147
Winning team probabilities / base rates (Experiments 7, 9, 11, 14-19).................... 147
Prediction strategy (Experiments 3-6, 8, 10, 12) 151
“Global” and “local” considerations (Experiments 1-16, E1-E8) 151
“This time” vs. “usually” considerations (Experiments 17-19)................................ 154
Confidence and motivation (Experiments 3-19, E1-E8).. 157
Thinking carefully and effortfully (Experiments 13, 14, 19)................................... 159
Outcome variability (Experiments 8, 10)... 161
Outcome usefulness for predicting the winning team (Experiments 8, 10)............. 163
Team liking (Experiment 12).. 164
Self-reported sports following and knowledge (Experiments 6-19, E5-E8)............. 167
Measured knowledge (Experiments 1-19, E1-E8)... 168
Maximizing Tendency Scale (Experiments 1-2) 172
Gender and age (Experiments 1-19, E1-E8).. 174
Instruction difficulty/confusion (Experiments 7, 9, 11, 14-19) 174
Contact for future studies (Experiments 1-19, E1-E8) 176
APPENDIX A3. ALTERNATIVE ANALYSES 177
Summary of experimental results 178
Does predicting scores make winner predictions worse? 185
Does predicting other event details make predictions worse?................................. 187
Are predictions worse because people pay less attention? 189
Are predictions worse because people think harder?... 191
Are predictions worse because people think less globally or more locally? 193
Do people who make detailed predictions use useful information less? 193
Which games will show the effect? 197
REFERENCES 199

LIST OF TABLES

Tables in the main text

Table 1. Experiments 1-19: Percentage of participants making wise predictions in each prediction condition. 26

Table 2. Experiments 1-5, 7-11, and 13-19: How much weight participants in the Winner condition gave to win/loss records and home field advantage when making predictions. 41

Table 3. Experiments 1-5, 7-11, and 13-19: Differences in information weights from the Winner condition in the detailed prediction conditions. 43

Tables in Appendix A1: Experimental instructions and designs

Table A1 1. Experiment 1 design. 60

Table A1 2. Experiment 2 design. 63

Table A1 3. Experiment 3 design. 67

Table A1 4. Experiment 4 design. 71

Table A1 5. Experiment 5 design. 75

Table A1 6. Experiment 6 design. 79

Table A1 7. Experiment 7 design. 82

Table A1 8. Experiment 8 design. 85

Table A1 9. Experiment 9 design. 89

Table A1 10. Experiment 10 design. 90

Table A1 11. Experiment 11 design. 90

Table A1 12. Experiment 12 design. 91

Table A1 13. Experiment 13 design. 94

Table A1 14. Experiment 14 design. 99

Table A1 15. Experiment 15 design. 100

Table A1 16. Experiment 16 design. 105

Table A1 17. Experiment 17 design. 111

Table A1 18. Experiment 18 design. 115

Table A1 19. Experiment 19 design. 116

Table A1 20. Experiment E1 design. 121

Table A1 21. Experiment E2 design. 124

Table A1 22. Experiment E3 design. 124

Table A1 23. Experiment E4 design. 125

Table A1 24. Experiment E5 design. 130

Table A1 25. Experiment E6 design. 133

Table A1 26. Experiment E7 design. 139

Table A1 27. Experiment E8 design. 143

Tables in Appendix A2: Additional measures

Table A2 1. Average % of winning team probabilities that agreed with the market favorite. 150

Table A2 2. Average % of winning team probabilities that were consistent with the participants' own predictions. 150

Table A2 3. Means and standard deviations of "global" and "local" considerations...... 153

Table A2 4. Correlations of "global" and "local" considerations with winning team prediction quality. 154

Table A2 5. Means and standard deviations of "this time" and "usually" considerations. 156

Table A2 6. Correlations of "this time" and "usually" considerations with winning team prediction quality. 156

Table A2 7. Means and standard deviations of confidence and motivation. 158

Table A2 8. Correlations of confidence and motivation with winning team prediction quality. 158

Table A2 9. Means and standard deviations of careful and effortful thinking. 160

Table A2 10. Correlations of careful and effortful thinking with winning team prediction quality. 161

Table A2 11. Means and standard deviations of outcome variability. 162

Table A2 12. Correlations of outcome variability with winning team prediction quality. 162

Table A2 13. Means and standard deviations of outcome usefulness for predicting the winning team. 163

Table A2 14. Correlations of outcome usefulness for predicting the winning team with winning team predictions quality. 164

Table A2 15. Means and standard deviations of liking ratings by country. 165

Table A2 16. Effect of liking on winning team prediction quality. 166

Table A2 17. Means and standard deviations of self-reported sports knowledge and following. 168

Table A2 18. Correlations of self-reported sports knowledge and following with winning team prediction quality. 168

Table A2 19. Means and standard deviations of measured knowledge scores. 171

Table A2 20. Correlations of measured sports knowledge with winning team prediction quality. 172

Table A2 21. Summary of responses to question difficulty. 175

Tables in Appendix A3: Alternative analyses

Table A3 1. Game-Level Analyses. Experiments 1-19: The average percentage of participants making wise predictions in each prediction condition for each experiment.. 179

Table A3 2. Participant-Level Analyses. Experiments 1-19: The average percentage of wise predictions made by participants in each prediction condition for each experiment.. 181

Table A3 3. Prediction-Level Analyses. Experiments 1-19: The percentage of wise predictions made in each prediction condition for each experiment. 183

Table A3 4. Game-Level Analyses. Experiments 2-19: The average percentage of participants making wise predictions in the Winner and Score + Winner conditions. 185

Table A3 5. Participant-Level Analyses. Experiments 2-19: The average percentage of wise predictions made by participants in the Winner and Score + Winner conditions. 186

Table A3 6. Prediction-Level Analyses. Experiments 2-19: The percentage of wise predictions made in the Winner and Score + Winner conditions. 186

Table A3 7. Game-Level Analyses. Experiments 4, 5, 8, 10, 15, and 16: The average percentage of participants making wise predictions in the Winner, Score + Winner, and Relevant + Winner conditions.. 187

Table A3 8. Participant-Level Analyses. Experiments 4, 5, 8, 10, 15, and 16: The average percentage of wise predictions made by participants in the Winner, Score + Winner, and Relevant + Winner conditions.. 188

Table A3 9. Prediction-Level Analyses. Experiments 4, 5, 8, 10, 15, and 16: The percentage of wise predictions made in the Winner, Score + Winner, and Relevant + Winner conditions.. 188

Table A3 10. Game-Level Analyses. Experiments 5 and 15-18: The average percentage of participants making wise predictions in the Winner, Score + Winner, and Irrelevant + Winner conditions.. 189

Table A3 11. Participant-Level Analyses. Experiments 5 and 15-18: The average percentage of wise predictions made by participants in the Winner, Score + Winner, and Irrelevant + Winner conditions. 190

Table A3 12. Prediction-Level Analyses. Experiments 5 and 15-18: The percentage of wise predictions made in the Winner, Score + Winner, and Irrelevant + Winner conditions. 190

Table A3 13. Game-Level Analyses. Experiments 13, 14, and 19: The average percentage of participants making wise predictions in the Winner and Score + Winner conditions for low- versus high-incentives. 191

Table A3 14. Participant-Level Analyses. Experiments 13, 14, and 19: The average percentage of wise predictions made by participants in the Winner and Score + Winner conditions for low- versus high-incentives. 192

Table A3 15. Prediction-Level Analyses. Experiments 13, 14, and 19: The percentage of wise predictions made in the Winner and Score + Winner conditions for low- versus high-incentives. 192

Table A3 16. Game-Level Analyses. Experiments 1-5, 7-11, and 13-19: The change in the percentage of participants in the Winner condition choosing the team to win based on win/loss records and home field advantage. 193

Table A3 17. Participant-Level Analyses. Experiments 1-5, 7-11, and 13-19: The average weights participants in the Winner condition gave to win/loss records and home field advantage. 194

Table A3 18. Prediction-Level Analyses. Experiments 1-5, 7-11, and 13-19: The weights given to win/loss records and home field advantage in the Winner condition. 194

Table A3 19. Game-Level Analyses. Experiments 1-5, 7-11, and 13-19: Differences from the Winner condition in the change in the percentage of participants choosing the team to win based on win/loss records and home field advantage. 195

Table A3 20. Participant-Level Analyses. Experiments 1-5, 7-11, and 13-19: Differences from the Winner condition in the average weights given to win/loss records and home field advantage. 195

Table A3 21. Prediction-Level Analyses. Experiments 1-5, 7-11, and 13-19: Differences from the Winner condition in the weights given to win/loss records and home field advantage. 196

Table A3 22. Game-Level Analyses. Experiments 1-19: The percentage of participants making wise predictions by prediction condition and which team had the better record. 197

Table A3 23. Participant-Level Analyses. Experiments 1-19: The average percentage of wise predictions made by participants by prediction condition and which team had the better record. 198

Table A3 24. Prediction-Level Analyses. Experiments 1-19: The percentage of wise predictions made by prediction condition and which team had the better record. ... 198

LIST OF FIGURES

Figures in the main text

Figure 1. Example of the Winner and Score + Winner conditions (Experiment 4).......... 19

Figure 2. Experiments 1-19: The difference in the percentage of wise predictions in the Winner vs. Score conditions. 28

Figure 3. Experiments 4, 5, 8, 10, 15, and 16: The average percentage of participants making wise predictions in the Winner, Score + Winner, and Relevant + Winner conditions. 31

Figure 4. Experiments 5 and 15-18: The average percentage of participants making wise predictions in the Winner, Score + Winner, and Irrelevant + Winner conditions. 34

Figure 5. Experiments 13, 14, and 19: The average percentage of participants making wise predictions in the Winner and Score + Winner conditions for low- versus high-incentives. 37

Figure 6. Experiments 1-5, 7-11, and 13-19: The increase in the likelihood of predicting a team to win when it had the better record and when it was the home team for Winner vs. Score conditions (A), Winner vs. Relevant detailed conditions (B), and Winner vs. Irrelevant detailed. 43

Figure 7. Experiments 1-5, 7-11, and 13-19: The percentage of participants predicting that the home team would win by prediction condition and difference in win/loss records. 45

Figure 8. Experiments 1-19: The percentage of participants making wise predictions by whether the home team also had the better record. 46

Figures in Appendix A1: Experimental instructions and designs

Figure A1 1. Example Experiment: Informed consent. 51

Figure A1 2. Example Experiment: Winner condition instructions. 52

Figure A1 3. Example Experiment: Winner condition predictions. 52

Figure A1 4. Example Experiment: Score + Winner condition instructions. 53

Figure A1 5. Example Experiment: Score + Winner predictions. 53

Figure A1 6. Example Experiment: Prediction strategy. 54

Figure A1 7. Example Experiment: “Global” and “local” considerations........................ 54

Figure A1 8. Example Experiment: Winner condition confidence and motivation. 55

Figure A1 9. Example Experiment: Score + Winner condition confidence and motivation. 55

Figure A1 10. Example Experiment: Self-reported following and knowledge. 56

Figure A1 11. Example Experiment: Measured knowledge. 57

Figure A1 12. Example Experiment: Gender, age, and contact....................................... 58

Figure A1 13. Example Experiment: Survey completion. 58

Figure A1 14. Experiment 1: Winner condition predictions.. 61

Figure A1 15. Experiment 1: Score Only condition predictions. 62

Figure A1 16. Experiment 2: Winner condition predictions.. 64

Figure A1 17. Experiment 2: Score Only condition predictions. 65

Figure A1 18. Experiment 2: Score + Winner condition predictions. 66

Figure A1 19. Experiment 3: Winner condition predictions.. 67

Figure A1 20. Experiment 3: Score Only condition predictions. 68

Figure A1 21. Experiment 3: Score + Winner condition predictions (incentivized for correct winning team selection). 69

Figure A1 22. Experiment 3: Score + Winner condition predictions (incentivized for correct exact final score). 70

Figure A1 23. Experiment 4: Winner condition predictions.. 71

Figure A1 24. Experiment 4: Score + Winner condition predictions. 72

Figure A1 25. Experiment 4: Hits + Winner condition instructions................................ 73

Figure A1 26. Experiment 4: Hits + Winner condition predictions................................. 73

Figure A1 27. Experiment 4: Runs + Winner condition instructions. 74

Figure A1 28. Experiment 4: Runs + Winner condition predictions. 74

Figure A1 29. Experiment 5: Winner condition predictions.. 75

Figure A1 30. Experiment 5: Score + Winner condition predictions. 76

Figure A1 31. Experiment 5: Runs + Winner condition predictions. 77

Figure A1 32. Experiment 5: Time + Winner instructions. 78

Figure A1 33. Time + Winner condition predictions... 78

Figure A1 34. Experiment 6: Winner condition predictions (with records). 79

Figure A1 35. Experiment 6: Score + Winner condition predictions (with records)........ 80

Figure A1 36. Experiment 6: Winner condition predictions (without records). 81

Figure A1 37. Experiment 6: Score + Winner condition predictions (without records). . 81

Figure A1 38. Experiment 7: Winner condition predictions.. 82

Figure A1 39. Experiment 7: Score + Winner condition predictions. 83

Figure A1 40. Experiment 7: Base rates instructions (all conditions). 84

Figure A1 41. Experiment 7: Base rates (all conditions)... 84

Figure A1 42. Experiment 8: Winner condition predictions.. 85

Figure A1 43. Experiment 8: Score + Winner condition predictions. 86

Figure A1 44. Experiment 8: Hits + Winner condition predictions................................. 87

Figure A1 45. Experiment 8: Runs + Winner condition predictions. 88

Figure A1 46. Experiment 12: Winner condition predictions.. 92

Figure A1 47. Experiment 12: Score + Winner condition predictions. 93

Figure A1 48. Experiment 13: Winner condition instructions (small bonus). 95

Figure A1 49. Experiment 13: Winner condition predictions (small bonus). 95

Figure A1 50. Experiment 13: Winner condition instructions (large bonus). 96

Figure A1 51. Experiment 13: Winner condition predictions (large bonus). 96

Figure A1 52. Experiment 13: Score + Winner condition instructions (small bonus). 97

Figure A1 53. Experiment 13: Score + Winner condition predictions (small bonus). 97

Figure A1 54. Experiment 13: Score + Winner condition instructions (large bonus). 98

Figure A1 55. Experiment 13: Score + Winner condition predictions (large bonus). 98

Figure A1 56. Experiment 15: Winner condition predictions. 101

Figure A1 57. Experiment 15: Score + Winner condition predictions. 102

Figure A1 58. Experiment 15: Free Throws + Winner condition instructions. 103

Figure A1 59. Experiment 15: Free Throws + Winner condition predictions. 103

Figure A1 60. Experiment 15: Temperature + Winner condition instructions. 104

Figure A1 61. Experiment 15: Temperature + Winner condition predictions. 104

Figure A1 62. Experiment 16: Winner condition predictions. 106

Figure A1 63. Experiment 16: Score + Winner condition predictions. 107

Figure A1 64. Experiment 16: Saves + Winner condition instructions. 108

Figure A1 65. Experiment 16: Saves + Winner condition predictions. 108

Figure A1 66. Experiment 16: Crowd + Winner condition instructions. 109

Figure A1 67. Experiment 16: Crowd + Winner condition predictions. 109

Figure A1 68. Experiment 16: Base rates (all conditions). 110

Figure A1 69. Experiment 17: Winner condition predictions. 111

Figure A1 70. Experiment 17: Score + Winner condition predictions. 112

Figure A1 71. Experiment 17: Temperature + Winner condition predictions. 112

Figure A1 72. Experiment 17: July 4th + Winner condition instructions....................... 113

Figure A1 73. Experiment 17: July 4th + Winner condition predictions. 113

Figure A1 74. Experiment 17: Base rates (all conditions). 114

Figure A1 75. Experiment 19: Bonus instructions... 117

Figure A1 76. Experiment 19: Winner condition predictions (small bonus)................. 117

Figure A1 77. Experiment 19: Winner condition predictions (large bonus). 118

Figure A1 78. Experiment 19: Score + Winner condition predictions (small bonus). ... 118

Figure A1 79. Experiment 19: Score + Winner condition predictions (large bonus). 119

Figure A1 80. Experiment 19: Base rates (all conditions). 119

Figure A1 81. Experiment E1: Winner condition predictions. 121

Figure A1 82. Experiment E1: Score + Winner condition predictions. 122

Figure A1 83. Experiment E1: Points + Winner condition instructions. 123

Figure A1 84. Experiment E1: Points + Winner condition predictions. 123

Figure A1 85. Experiment E4: Winner condition predictions (NBA). 126

Figure A1 86. Experiment E4: Score + Winner condition predictions (NBA). 127

Figure A1 87. Experiment E4: Winner condition predictions (NHL). 128

Figure A1 88. Experiment E4: Score + Winner condition predictions (NHL). 129

Figure A1 89. Experiment E5: Winner condition predictions. 130

Figure A1 90. Experiment E5: Score + Winner condition predictions. 131

Figure A1 91. Experiment E5: Crowd + Winner condition instructions. 132

Figure A1 92. Experiment E5: Crowd + Winner condition predictions. 132

Figure A1 93. Experiment E6: Winner condition predictions (no majority winner prediction). 133

Figure A1 94. Experiment E6: Score + Winner condition predictions (no majority winner prediction). 134

Figure A1 95. Experiment E6: Winner condition instructions (with majority winner prediction). 135

Figure A1 96. Experiment E6: Winner condition predictions (with majority winner prediction). 136

Figure A1 97. Experiment E6: Score + Winner condition instructions (with majority winner prediction). 137

Figure A1 98. Experiment E6: Score + Winner condition predictions (with majority winner prediction). 138

Figure A1 99. Experiment E7: Winner condition predictions (no majority winner prediction). 139

Figure A1 100. Experiment E7: Score + Winner condition predictions (no majority winner prediction). 140

Figure A1 101. Experiment E7: Winner condition predictions (with majority winner prediction). 141

Figure A1 102. Experiment E7: Score + Winner condition (with majority winner prediction). 142

Figure A1 103. Experiment E8: Winner condition predictions. 143

Figure A1 104. Experiment E8: Score + Winner condition predictions. 144

Figure A1 105. Experiment E8: Free Throws + Winner condition instructions. 145

Figure A1 106. Experiment E8: Free Throws + Winner condition predictions. 145

Figure A1 107. Experiment E8: Temperature + Winner condition instructions. 146

Figure A1 108. Experiment E8: Temperature + Winner condition predictions. 146

Figures in Appendix A2: Additional measures

Figure A2 1. Winning team probability instructions. 148

Figure A2 2. Winning team probability question format (Experiments 7, 9, 11, and 14-15). 149

Figure A2 3. Winning team probability question format (Experiments 16-19). 149

Figure A2 4. Prediction strategy question format. 151

Figure A2 5. "Global" and "local" considerations question format. 152

Figure A2 6. "This time" and "usually" considerations question format. 155

Figure A2 7. Confidence and motivation question format. 157

Figure A2 8. Thinking carefully and effortfully question format. 160

Figure A2 9. Outcome variability instructions. 162

Figure A2 10. Outcome variability question format. 162

Figure A2 11. Outcome usefulness for predicting the winning team question format. .. 163

Figure A2 12. Team liking question format. 164

Figure A2 13. Self-reported sports following and knowledge question format. 167

Figure A2 14. Histograms of responses for self-reported sports knowledge and following. 167

Figure A2 15. Measured sports knowledge instructions. 170

Figure A2 16. Example of measured knowledge question format (team/division matching). 170

Figure A2 17. Example of measured knowledge question format (player/team matching). 170

Figure A2 18. Histogram of measured knowledge scores. 171

Figure A2 19. Maximizing Tendency Scale question format. 173

Figure A2 20. Gender and age question format. 174

Figure A2 21. Question difficulty question format (Experiment 7). 175

Figure A2 22. Question difficulty question format (Experiments 9, 11, and 14-19)...... 175

Figure A2 23. Contact for future studies sport selection. 176

Figure A2 24. Contact for future studies e-mail entry. 176

INTRODUCTION

Good decisions often depend on good predictions. For example, an investment decision hinges on one's forecast of the market, an admission decision hinges on one's forecast of an applicant's success, and a consumer choice hinges on one's forecast of a product's quality. Thus, understanding the factors that affect prediction quality can also help people make better decisions.

In this paper, we will demonstrate that making *detailed predictions* about an event can make other predictions about that event worse. For example, asking people to predict how many hits each baseball team will get in an upcoming game (a detailed prediction) before predicting which team will win the game (a more general prediction) can make their winning team predictions worse. This suggests that, counter to lay beliefs, thinking through as many details about an event as possible could do more harm than good.

Prior research on detailed predictions

The question of whether asking more detailed prediction questions makes predictions worse was first investigated by Yoon, Suk, Goo, Lee, and Lee (2013). Specifically, they investigated whether more detailed *versions* of prediction questions led to less accurate predictions about general outcomes. For example, predicting the final score of a soccer game is a more detailed version of predicting the winning team because it not only requires forecasters to determine which team they think will win, but also requires them to consider additional details (e.g., whether it will be a low- or high-scoring game, how many runs the victor will win by, etc.). In their investigation, Yoon and colleagues (2013) asked participants to predict the outcomes of soccer games by either simply indicating whether they thought the home team would win, lose, or tie the game, or by entering the exact final score of the game.[1] In three experiments (N = 65, N = 86, N = 100 participants; n = 16, n = 18, n = 16 games), they found that winning team predictions were less accurate when participants predicted the final score than when they simply indicated a win, loss, or tie for the home team (p = .019, p = .037, p = .045). That is, giving a more detailed version of the winning team prediction (i.e., the score) worsened winning team prediction accuracy.

Yoon and colleagues claimed that this effect occurred because predicting scores is more difficult and therefore makes people think *too hard* about which team will win, and that thinking harder about their predictions made their predictions worse (e.g., Dijksterhuis, Bos, Nordgren, & van Baaren, 2006; Dijksterhuis, Bos, van der Leij, & van Baaren, 2009). However, as we will explain in more detail later, problems with their design coupled with the fact that their samples were too small to reliably detect differences in prediction accuracy means that whether and how detailed predictions affect predictions about more general outcomes are open questions. We propose that making detailed predictions makes forecasts of more general outcomes worse because doing so brings to mind additional information that is not useful for predicting which team will win the game. Furthermore, forecasters use this relatively useless information in their predictions, meaning that they necessarily give less weight to more important information. For example, asking people to predict how many hits each baseball team will get might lead them to think about the quality of each teams' pitchers and batters, and so when they are subsequently asked to predict the winning team, information about pitchers and batters is top-of-mind and therefore used in their forecasts. Importantly, while this

[1] Yoon et al. (2013) refer to score predictions as "specific" predictions rather than "detailed" predictions.

information might be diagnostic in isolation, it would provide little or no diagnostic information over and above the information already contained within the teams' win/loss records given that the quality of the teams' players directly affects how many games they win.[2] Therefore, we propose that detailed predictions can make predictions about other outcomes worse by causing forecasters to think about and use relatively useless information in their predictions, taking focus away from more predictively valid information (e.g., the teams' win/loss records).

This hypothesis stems from three well-established findings from the psychology of forecasting. First, people do not (and often cannot) consider all of the relevant information when making predictions. Second, the information that people do consider tends to be the information that is most accessible in memory, even if this information is not the most predictively valid information available. Finally, forecasters are largely unable to accurately weigh each piece of information according to its predictive value, meaning that they tend to give too much weight to less useful information and too little weight to more useful information in forecasts. Together, these three tendencies suggest that drawing people's attention to less important details about an event should make predictions about more general outcomes worse. Importantly, in this account people are not thinking more or less hard about their predictions. Rather, they are simply thinking about different information and using that information suboptimally.

[2] It should also be noted that people often overestimate the value of redundant information for forecasting and thus give redundant information too much weight in their predictions (Kahneman & Tversky, 1973; Slovic, 1966; Soll, 1999).

Forecasters only consider a subset of relevant information

When trying to predict the outcome of a future event, people are naturally inclined to imagine ways in which that event might unfold. For example, people trying to predict how much they would enjoy going on a camping trip with friends might first imagine what activities they would do on the trip, what the weather would be like, how well everyone would get along, etc. Furthermore, people use how easy it is to imagine scenarios leading to a certain outcome (e.g., enjoying the trip) to estimate how likely that outcome is to occur, and so people rely heavily on the scenarios that they happen to imagine to make predictions about the future (Kahneman & Tversky 1981; Tversky & Kahneman 1973). However, people tend to only consider a handful of possible scenarios, and potentially important but unimagined scenarios are not incorporated into forecasts, leading to poor and inconsistent predictions (for reviews, see Dunning, 2007; Kahneman & Lovallo, 1993; Lagnado & Sloman, 2004; Lovallo & Kahneman, 2003). Thus, this scenario-based method of forecasting is vulnerable to a variety of errors stemming from the forecaster's inability to exhaustively consider all of the relevant information for the prediction.

One example of such an error is focusing too narrowly on the target event and failing to consider other factors that, while not directly related to the event, would significantly affect outcomes. For example, when trying to predict how long it will take to complete a shopping trip, people are likely to build scenarios around things that are directly related to "getting shopping done" such as driving to the store, looking for products, waiting in line at checkout, etc., but are unlikely to consider other intervening factors that would also affect how long it takes them to shop, such as getting stuck in traffic or coming down with a cold (Dunning, 2007). Similarly, past research has found that when people try to predict how much an event will affect their future well-being, they focus too heavily on the direct impact of the event itself but fail to consider that other events in their lives will also contribute to their overall well-being (Schkade & Kahneman, 1998; Wilson & Gilbert, 2005; Wilson, Wheatley, Meyers, & Gilbert, 2000). For example, Wilson and colleagues (2000) found that college football fans overestimated how long their emotional well-being would be affected by their football team winning or losing a game because they largely did not consider how other future events would also affect their happiness (e.g., studying for exams, going to parties).

Forecasters also have difficulty considering information that is either abstract or not explicitly presented to them at the time of the prediction. For example, when estimating the likelihood that a complex system such as a car will fail, one strategy is to construct a "fault tree" by listing all the things that could go wrong, such as "dead battery" or "defective fuel system" (concrete causes), and adding a category for "all other problems" (abstract causes). Then, the forecaster estimates the probability of failure for each category to determine the total probability of failure for the entire system. However, Fischhoff, Slovic, & Lichtenstein (1978) found that people did not appropriately transfer probabilities to the "all other problems" category when some of the concrete causes for failure were omitted from the fault tree. To illustrate with a simplified example, if comparing a tree that consists of "dead battery", "defective fuel system", and "all other problems" to a pruned tree consisting of only "dead battery" and "all other problems", the probability given to "all other problems" in the pruned tree would be considerably lower than the sum of the probabilities given to "defective fuel system" and "all other problems" in the full tree. In fact, the participants in Fischhoff et al.'s (1978) experiments were largely insensitive to what information was missing from fault trees and therefore significantly underestimated the probability of a system failure in trees that listed fewer concrete sources of failure. Fischhoff and colleagues (1978) concluded that scenarios that are not explicitly presented to forecasters are "out of sight, out of mind", and are not incorporated into forecasts. Importantly, even though people were able to improve their predictions by generating their own list of concrete causes belonging to the "all other problems" category (Dube-Rioux & Russo, 1988), they did not appear to do so unless explicitly prompted.

Additionally, one of the most common omissions from forecasters' predictions about the future is information about what has happened in similar situations in the past (Dunning, 2007; Kahneman & Lovallo, 1993; Lagnado & Sloman, 2004; Lovallo & Kahneman, 2003). For example, imagine someone wants to predict how long it will take her to complete a work project. Rather than considering all of the factors that might influence how the project would progress (e.g., what resources she has at her disposal, the availability of her teammates, what other tasks will be competing for her attention, etc.), she could instead base her prediction on how long it has taken her to complete similar projects in the past. Buehler and Griffin (2003), however, found that when people predicted how long it would take them to complete tasks such as Christmas shopping or class assignments, they mostly reported thinking about what they expected to happen in the future and rarely reported thinking about how long it took them to complete similar tasks in the past (see also Buehler, Griffin, & Ross, 1994). Furthermore, participants who were asked to think about their future plans made significantly less accurate predictions than those who were not. In fact, in many if not most cases, thinking about the outcomes of similar past events generates superior predictions than imagining what might happen in the future (Dawes, 1996; Grove, Zald, Lebow, Snitz, & Nelson, 2000; Lovallo & Kahneman, 2003; Meehl, 1954). This is partially because the kinds of information that forecasters frequently fail to consider usually has similar effects on the likelihood of certain outcomes occurring in the future as they did on those outcomes occurring in the past. However, information about past cases is rarely used as the basis for forecasts (Dawes, 1996; Grove & Meehl, 1996; Lagnado & Sloman, 2004).

Forecasters use the information that is most accessible in memory

Given that people only consider a subset of the information available to them when making predictions, it is important to understand the factors that influence what information they think about. As mentioned in the previous section, the easier it is to imagine scenarios leading to a certain outcome, the greater the perceived likelihood is that the outcome will occur. This means that predictions are primarily influenced by the information that comes most easily to mind, and so the outcomes or scenarios that are most available (or "accessible") in memory get incorporated into forecasts.

Indeed, research on this *availability heuristic* has frequently demonstrated that incidents that come to mind easily are judged to be more likely (Morewedge & Todorov, 2012; Plous, 1993; Tversky & Kahneman, 1973; Tversky & Kahneman, 1974). There are multiple factors that contribute to what information becomes readily available in memory. The most straightforward reason is that some cue is frequently observed in conjunction with a particular outcome, and over time, people learn the association between the cue and the outcome (i.e., the cue is "ecologically valid"; Bruswick & Kamiya, 1953). For example, people who see dark clouds outside will predict a high chance of rain because they have observed throughout their lives that dark clouds are usually followed by rain. In such cases, these cues (e.g., dark clouds) are highly available because they are truly correlated with outcomes (e.g., rain).

However, there are other factors that affect the availability of information in memory that are not related to how likely different outcomes are, such as how vividly and how recently an event was observed. For example, the judged likelihood of being in a car accident goes up immediately after seeing an overturned car on the side of the road, and people believe that shark attacks and plane crashes are more likely than they actually are because these events are featured prominently in the news (Plous, 1993; Tversky & Kahneman, 1973). Similarly, people erroneously estimate that there are more words that begin with the letter “r” than words that have “r” as the third letter because it is easier to generate instances of the former case (e.g., red, rabbit, radio) than the latter (e.g., card, three, perfume; Tversky & Kahneman, 1973). In another illustration of the use of non-predictive but highly available information, Morewedge and Todorov (2012) found that people over-weighted atypical past behaviors in predictions about future behaviors because atypical behaviors are more memorable, and Bastardi and Shafir (1998) found that choosing to wait for information (e.g., waiting to find out the exact amount of debt a mortgage applicant has) made this information more cognitively available and increased its weight in judgments. Together, these findings mean that the most available information is not always the most important information, but even so it is still likely to be used in forecasts. Thus, increasing the availability of relatively unimportant information should make predictions worse.

Also, because recently formed judgments are more available in memory, judgments that people make earlier can have a downstream influence on subsequent judgments. For example, in Feldman and Lynch's (1988) *accessibility-diagnosticity* framework, answers to previous questions are often used to approximate the answers to subsequent similar questions in surveys (e.g., I might not immediately know how much I value animal welfare, but I just told someone that I love dogs, so I am probably willing to donate $10 to the Animal Welfare Society). This is because preferences and beliefs are constructed on the spot unless a pre-existing preference or belief is accessible in memory and sufficiently diagnostic for the question at hand, in which case the pre-existing cognition will be used instead. In fact, past research has identified several cases and conditions in which answers to prior questions are used to approximate answers to subsequent questions (Lynch, Marmorstein, and Weigold 1988; Menon & Raghubir, 2003; Menon, Raghubir, & Schwarz, 1995; Simmons, Bickart, and Lynch, 1993). Also, as with the literature on the availability heuristic, Feldman and Lynch (1988) identify that other determinants of the accessibility of information in memory include how recently it was activated, how vivid it is, cues from the environment (e.g., priming), etc. This means that not only will recent judgments be highly accessible, but the information that was used to make them will also be more accessible as well. These findings suggest that when forecasters make predictions that are similar to other recent predictions, their previous predictions and the information they considered when making them will be highly accessible in memory and therefore likely to be used in their subsequent forecasts.

Forecasters do not weigh information properly

So far we have discussed how forecasters only use a subset of available information, and how the information they use is heavily influenced by what is most accessible in memory. Another important component of forecasting, however, is *how* people use the information they think about. Even if people were capable of considering all of the relevant information about a prediction, they would still have a hard time weighing that information properly. A wealth of past research has found that, in both judgments and predictions, people tend to assign suboptimal weights to the information they consider.

For example, research on the *dilution effect* shows that giving people information that provides little or no additional predictive power generally makes their predictions worse (Edgell et al., 1996; Nisbett, Zukier, & Lemley, 1981; Troutman & Shanteau, 1977; Zukier, 1982). For example, Nisbett and colleagues (1981) had graduate students in social work rate the likelihood that a hypothetical client was a child abuser based on information that was judged by other social work students to be diagnostic (e.g., "he was abused by his stepfather") and information that was judged to be nondiagnostic (e.g., "he manages a hardware store"). They found that, holding the amount of diagnostic information constant, increasing the amount of nondiagnostic information about the client decreased his judged likelihood of being an abuser. Indeed, this detrimental effect of adding nondiagnostic information to predictions has been found across a wide variety of domains, including accounting (Hackenbrack, 1992; Hoffman & Patton, 1997; Shelton, 1999), legal decisions (Smith, Stasson, & Hawkes, 1998), and consumer choice (Meyvis & Janiszewski, 2002).

One explanation given to why adding nondiagnostic information makes predictions worse is that doing so makes the target seem more or less representative of various outcomes (Lichtenstein, Earl, & Slovic, 1975; Nisbett et al., 1981; but see also Tetlock, Lerner, & Boettger, 1996). The *representativeness heuristic* proposed by Tversky and Kahneman is a mental shortcut whereby people base their judgments and predictions on how similar (i.e., representative) a situation is to a particular outcome, or how similar a target is to a particular category (Kahneman & Tversky, 1972; Kahneman & Tversky, 1973; Tversky & Kahneman, 1971; Tversky & Kahneman, 1974). For example, people judge the likelihood that a man named Tom is an engineer versus a lawyer based on how well characteristics about Tom (e.g., that he likes mathematical puzzles) are representative of a stereotypical engineer versus a stereotypical lawyer (Kahneman & Tversky, 1973). In many cases, judgments of representativeness override more objective information about the distribution of outcomes in the population (e.g., Tom was selected from a population that contains 70% lawyers).

However, past research has demonstrated that adding nondiagnostic information makes predictions worse even in cases where judgments of representativeness are unaffected or irrelevant (Dana, Dawes, & Peterson, 2013; LaBella & Koehler, 2004; Nelson, Bloomfield, Hales, and Libby, 2001; Simmons & Lynch, 1991; Tetlock & Boettger, 1989). This is because, in general, people are bad at weighing different pieces of information relative to their predictive strength (Buehler et al., 1994; Griffin & Tversky, 1992; Grove et al., 2000; Helzer & Dunning, 2012; Hutchinson & Alba, 1991; Slovic, 1975; Slovic & Lichtenstein, 1971; Soll, 1999; Weaver, Garcia, & Schwarz, 2012; Yaniv, 2004), and give too much weight to information that has relatively low predictive power and too little weight to information that has relatively high predictive power. For example, Hall, Ariss, and Todorov (2007) found that participants who were only given the win/loss records and half-time scores of basketball games were better at predicting winning teams than participants who were additionally given the names of the teams. This was because, while the teams' identities (and therefore their reputations) did have some predictive power in isolation, they did not provide any predictive power over and above the information that was already available (the win/loss records and half time scores). However, participants did not seem to realize this and gave the team names too much weight in their predictions. Similarly, people are largely unable to discount the weight given to information that is largely redundant with existing information (Slovic, 1966; Slovic & Lichtenstein, 1971; Soll, 1999), and people also often give more weight to the strength of evidence (e.g., how positive a letter of recommendation is) than to the validity of evidence for predicting outcomes (e.g., how accurately recommendation letters predict future performance) (Griffin & Tversky, 1992; Nelson et al., 2001). Given that forecasters are bad at properly integrating and weighing information when making predictions, it stands to reason that drawing forecasters' attention to less important details about the outcomes they are trying to predict would make their predictions worse.

The present research: How do detailed predictions affect prediction quality?

While much research has shown that giving people non-diagnostic information worsens their predictions, our investigation focuses on how prediction quality might be affected by the way predictions are elicited. Specifically, we investigate whether asking people to make detailed predictions affects the quality of their predictions about other outcomes.

Although Yoon and colleague's (2013) finding that people who predicted final scores made less accurate winning team predictions than people who only selected winners seems to provide preliminary evidence that making detailed predictions can make other predictions worse, this evidence is limited. First, whereas participants in the "Winner" (non-detailed) condition were incentivized for correctly predicting the winning team, those in the "Score" (detailed) condition were incentivized for correctly predicting the exact final score. It is possible that participants in the Score condition were less motivated to think carefully about their predictions since predicting exact final scores is much harder (and therefore much less likely to pay off) than predicting winning teams. Second, because participants in the Score condition gave their predictions using a more complicated entry method (typing in each team's score) it is possible that they simply made more mistakes than those in the Winner condition. Finally, another potential problem with Yoon et al.'s design is their definition of prediction quality. In their studies, they assessed the quality of predictions by comparing the accuracy of predictions across conditions. However, accuracy in sports predictions is a very unreliable, and thus poor, measure of prediction quality; moreover, as we will later show, detecting differences in prediction accuracy would likely require hundreds of games and thousands of participants rather than the tens of games and participants recruited by Yoon and colleagues. Taken together, it is unclear whether Yoon et al.'s (2013) result would replicate using a better measure of prediction quality, and if so, whether it would emerge when the conditions have the same incentives and the same chance of making mistakes. This means that whether and how detailed predictions makes predictions about more general outcomes worse are open questions.

A few observations from past research on the psychology of forecasting suggests that making detailed predictions would have a detrimental effect on subsequent related predictions. First, people only consider a subset of relevant information when making predictions, and the information they think about depends on how available/accessible it is in their minds. This suggests that information considered when making detailed predictions will also be considered when making other similar predictions (so long as that information seems sufficiently relevant). For example, if people are first asked to predict how many hits each baseball team will get, they are likely to continue thinking about information related to how many hits each team will get when predicting which team will win the game.

Additionally, people do not weigh the information they think about properly, and tend to give too much weight to information that is relatively unimportant and therefore too little weight to information that is more important. This suggests that considering information that relatively unimportant for making the more general prediction will take weight away from more important information and make predictions worse.

To investigate the question of whether making detailed predictions actually makes predictions worse, we report the results of 19 experiments examining 415,960 predictions from 10,895 participants about the outcomes of 724 professional sporting events and find that making detailed predictions (e.g., the exact final score) does generally make winning team predictions worse as our theory suggests. Next, we will explore possible alternative explanations of this effect. We will show that detailed predictions do not worsen predictions by increasing inattention or fatigue, thinking too hard, or decreasing self-reported consideration of the teams' overall competencies. Instead, we will show that thinking about game-relevant details before predicting the winning team causes people to give less weight to important diagnostic information, presumably because the detailed information becomes more accessible in memory. Finally, we demonstrate that the dilution of more useful information means that not all games will show this effect, and that knowing how people use the information available to them allows us to predict what kinds of events will and will not be affected by detailed predictions.

GENERAL METHODS

In 19 experiments, we randomly assigned participants to make detailed or non-detailed predictions about upcoming sporting events and then examined whether people who made detailed predictions made worse predictions. Professional sports is a uniquely useful context for studying predictions because sporting events occur frequently, have a limited number of possible outcomes (win/lose/tie), yield timely and unambiguous results, and are easy to incentivize. It is also easy to find a large sample of participants who have some knowledge about the prediction context and are interested and motivated to predict the outcomes (i.e., sports fans).

In total, we collected 415,960 predictions about 724 sporting events. Ten experiments investigated predictions of Major League Baseball (MLB) games, five investigated predictions of National Hockey League (NHL) games, three investigated predictions of National Basketball Association (NBA) games, and one investigated predictions of Fédération Internationale de Football Association (FIFA) World Cup matches.

Sample

Across 19 experiments, we recruited 10,896 participants from Amazon's Mechanical Turk website for an average of 573 participants per experiment and 191 participants per experimental condition.[3] Most participants were male (71.7%) and the sample's average age was 32 years old (*SD* = 10.0).[4] Each study was advertised as a "survey for [sport] fans" because we wanted participants to have some knowledge about the sport they were predicting; however, they were not required to prove any knowledge about the sport to participate. Participants were paid 50 to 75 cents for completing each 10-20 minute survey and they earned an additional 5 cents for each correct winning team prediction (the few exceptions to this incentive scheme are described below). The average participant earned $1.72 (*SD* = $0.61) in total.

Procedure

All experiments had similar procedures.[5] In each study, participants were asked to predict the outcomes of 29-48 upcoming sports games (*M* = 38 games per study, *SD* = 6.7). We sought to have participants predict as many games as possible without making the survey too long and without asking them to predict games that were too far in the future, and so the number of games varied by the sport asked about in the experiment. For example, while there are about fifteen Major League Baseball games per day during the regular baseball season, the number of National Basketball Association and National

[3] We did not screen out participants who had participated in previous prediction studies because each new study required predictions about novel games, and we did not believe that participants needed to be blind to different conditions for the effect to occur. Furthermore, carryover effects between studies would lower the likelihood of finding significant differences between prediction conditions. Across our sample, 57.2% of participants had not previously participated in a prediction experiment.

[4] The age calculations exclude five participants who reported ages less than 18 and seven who reported ages greater than 100.

[5] The complete survey designs for each experiment are reported in Appendix A1.

Hockey League games per day varies considerably (typically between two and twelve games per day). As a consequence, experiments that asked about baseball games had participants predict 39-45 games (three days' worth) while experiments that asked about basketball or hockey games had participants predict 29-32 games (four days' worth). Participants made their predictions all at once 0-3 days before the games, with the exception of the 48 FIFA World Cup Group Stage predictions in Experiment 12, which were made 1-15 days before the games.

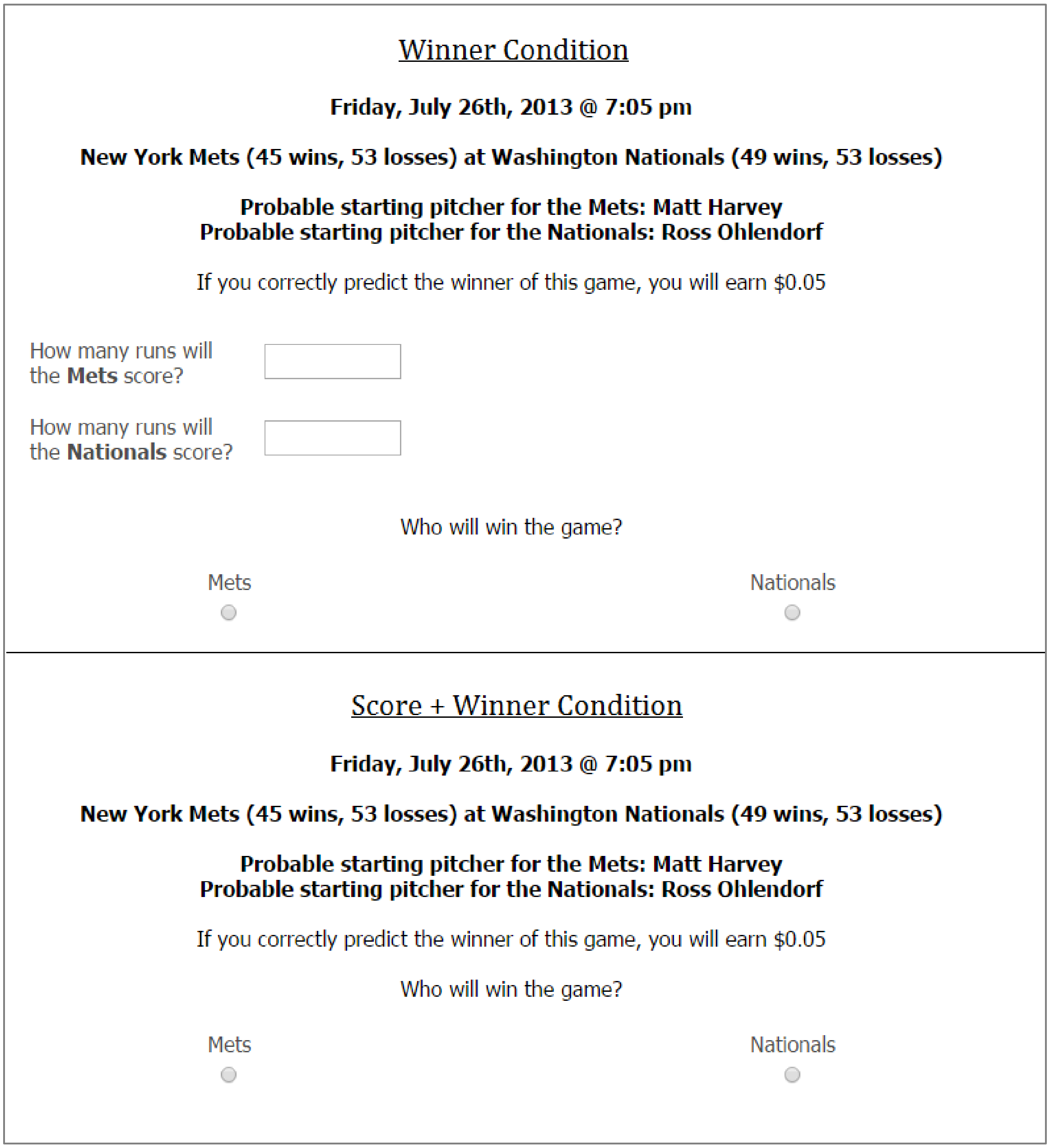
We manipulated how we elicited participants' predictions. In all experiments, we randomly assigned participants to make their predictions by either selecting the winning team for each game (the "Winner" condition) or by entering the final score for each game—a more detailed version of the winning team prediction (the "Score Only" or "Score + Winner" conditions).[6] Experiments 1-3 included a Score Only condition in which participants predicted each game's final score without separately selecting the winning team. In this condition, we inferred participants' winner predictions from their score predictions, as was done by Yoon and colleagues (2013). However, comparing winning team predictions between "Winner" and "Score Only" conditions is problematic because the mechanics of entering scores versus simply selecting winners could produce artifactual differences between conditions. For example, condition differences could emerge if participants are more likely to make errors when entering scores than when selecting winning teams. To remedy this, Experiments 2-19 included a "Score + Winner"

[6] Because Major League Baseball games, National Basketball Association games, and National Hockey League games cannot end in a draw, we did not allow participants to enter tied scores or select a tied game for these games (676 out of 724 in our sample). Because soccer games can end in a draw, we allowed participants to enter tied scores and select "Draw" for the 48 FIFA soccer games in our sample (Experiment 12).

condition in which participants both entered their predicted final score for a game and then separately selected their predicted winning team.[7] This allowed us to make an apples-to-apples comparison between the Winner condition's winner predictions and the Score + Winner condition's winner predictions. Figure 1 shows examples of the Winner and Score + Winner conditions.

[7] In every experiment except one (Experiment 2), participants in the Score + Winner condition predicted the score before predicting the game's winner. In Experiment 2, they predicted the score after predicting the game's winner.

Figure 1. Example of the Winner and Score + Winner conditions (Experiment 4).


Winner Condition

Friday, July 26th, 2013 @ 7:05 pm

New York Mets (45 wins, 53 losses) at Washington Nationals (49 wins, 53 losses)

Probable starting pitcher for the Mets: Matt Harvey
Probable starting pitcher for the Nationals: Ross Ohlendorf

If you correctly predict the winner of this game, you will earn $0.05

How many runs will the **Mets** score?

How many runs will the **Nationals** score?

Who will win the game?

Mets

Nationals

Score + Winner Condition

Friday, July 26th, 2013 @ 7:05 pm

New York Mets (45 wins, 53 losses) at Washington Nationals (49 wins, 53 losses)

Probable starting pitcher for the Mets: Matt Harvey
Probable starting pitcher for the Nationals: Ross Ohlendorf

If you correctly predict the winner of this game, you will earn $0.05

Who will win the game?

Mets

Nationals

All predictions were incentivized. Experiments 1-3 followed Yoon et al.'s (2013) incentive scheme of paying a smaller amount (5 cents) for each correct winning team prediction and a larger amount (40 cents) for each correct final score prediction.[8] In Experiment 3, we manipulated whether participants in the Score + Winner condition earned 5 cents for each correct winning team prediction or 40 cents for each correct final score prediction. Note that incentivizing different outcomes (exact final scores vs. winning teams) using different amounts (5 vs. 40 cents) across different conditions introduces potential confounds when comparing the quality of winning team predictions between conditions. For this reason, Experiments 4-19 held incentives constant across all conditions (5 cents for each correct winning team prediction, with the exception of three experiments described subsequently, in which the incentives were larger for half of the games). In these studies, we paid all participants in all conditions for correctly predicting the winning teams; they were never incentivized for accurately predicting any additional details (e.g., scores, hits, etc.).

As previously mentioned, the 19 experiments investigated different sports: baseball, basketball, hockey, and soccer. But they also differed in more meaningful ways. Most importantly, although all experiments included Winner and Score conditions, many experiments also included conditions in which participants predicted other details about the game in addition to predicting the winning team. We included these other conditions because we were interested in whether making *any* detailed predictions about the game would make winning team predictions worse. In some conditions, these detailed predictions were relevant to the game; for example, in three of the baseball experiments (Experiments 4, 8, and 10), participants in the Hits + Winner condition predicted both the

[8] Our payment amounts differed slightly from Yoon et al.'s, who paid 10 cents for each correct winning team prediction and 40 cents for each correct final score prediction.

number of hits each baseball team would accumulate and which team would win the game. In other conditions, the predicted details were irrelevant to the game; for example, in one of the hockey experiments (Experiment 16), participants in the Crowd + Winner condition predicted what percentage of the crowd at the game would be American citizens as well as the winning team. Our theory suggests that making any detailed predictions that are relevant to the game should make winning team predictions worse to the extent that they prompt forecasters to think about less useful information that gets incorporated into their subsequent winning team predictions. All detailed predictions were classified as either "relevant" or "irrelevant" *a priori*, and the conditions and predictions in each experiment are described in greater detail in the Results section and in the note to Table 1.

Experiments also varied in the information given to participants about each game. For all games, participants were told the date, start time, location, the visiting and home teams,[9] and, in the baseball experiments, the names of the starting pitchers.[10] In addition, although most experiments also gave participants each team's win/loss records (i.e., the numbers of games won and lost so far that season), Experiments 6 and 12 did not give

[9] Because Experiment 12 investigated FIFA World Cup matches that all took place in Brazil, only one team (Brazil's national team) out of 32 could be considered the "home" team. Thus, in this experiment, neither team was designated as "home" or "visiting".

[10] We also ran 8 additional experiments in which we gave participants each team's "Points Scored" (the total number of points scored by that team so far that season) and "Points Allowed" (the total number of points scored against that team so far that season) for football and hockey games, and each team's "Average Points Scored" (the average number of points scored by that team per game so far that season) and "Average Points Allowed" (the average number of points scored against that team per game so far that season) for basketball games. However, we chose not to include these experiments in our analyses because we are worried that differences between prediction conditions in these studies (namely, between Winner and Score + Winner) may have arisen because people who are asked about winners only look at the win/loss records and people who are asked about scores only look at the points scored or average points scored records. It should be noted that the effects we report are stronger when we include the data from these 8 experiments. The designs of these experiments included in Appendix A1.

any record information for the teams.[11] This allowed us to examine whether providing this information was necessary to produce the hypothesized effect.

Prediction Quality

We were interested in investigating whether making detailed predictions affects the quality of people's predictions. For this reason, in all experiments we compare participants' predictions to well-calibrated sports betting markets, which publish odds set by professional oddsmakers. For each game, oddsmakers use attributes such as team records, home field advantage, and other information to determine the probability that each team will win, and those probabilities are reflected in the odds that they set for each game. These odds provide accurate probability estimates: For example, the home team won 57.1% of the games when the odds indicated that they had a 55-60% chance of winning in our data. Importantly, these odds indicate which team is the "likely winner," meaning that it is more likely to win the game than the opposing team. In our analyses, predicting that the likely winner will win the game is considered a "wise" prediction.[12] In all experiments, we assess the wisdom of participants' *winning team predictions*, regardless of prediction condition and what other detailed predictions they made.

---

[11] Experiment 6 also had two conditions in which participants were given team records (wins, losses, points scored, and points allowed) and two conditions in which participants were not given any records. For the reasons stated in the previous footnote, only the two conditions that did not give record information are included in the analyses presented here. However, we found the same detrimental effect of predicting the score in both the conditions with records, $t(27) = 2.29$, $p = .030$, and without records, $t(27) = 3.16$, $p = .004$.

[12] We could have also defined a wise prediction as a prediction in favor of the team with the superior win/loss record. However, there are other important game attributes other than win/loss records that significantly affect the probability that a team will win. For example, one of the notable differences between predictions based on win/loss records and market odds is that sports betting markets take home field advantage—which is known to affect game outcomes—into account. For this reason, using market odds is the superior method of defining wise predictions. Indeed, the market odds are more correlated with actual game outcomes ($r(699) = 0.21$, $p < .001$) than records alone ($r(699) = 0.13$, $p < .001$). However, the patterns of results are largely consistent between the two specifications of wise predictions, and we report the results of the main analyses defining wise predictions as choosing the team with the better win/loss record in Appendix A3.

Of course, another possible measure of prediction quality is accuracy. And, indeed, this was the measure used by Yoon and colleagues (2013). However, accuracy is not an appropriate measure of prediction quality in this context, as a wise prediction is one that predicts that the most probable outcome will occur, regardless of whether that outcome actually occurs. To illustrate, consider a biased coin that comes up heads 60% of the time. A noisy and imprecise measure of prediction quality is whether someone's prediction about the outcome of the coin flip was accurate. A much better measure of prediction quality is whether they predicted "heads". Similarly, sports outcomes are extremely noisy—across the 724 games in our data, the likely winner won only 57.7% of the time—and so it would take many thousands of predictions about hundreds of games to detect whether one condition makes more accurate predictions than another.[13] In this case, a better measure of prediction quality is whether people predicted the teams that were most likely to win as opposed to the teams that actually won.[14]

Additional Measures

Winning Team Probabilities. In experiments 7, 9, 11, and 14-19, immediately after predicting the outcomes of all games, participants indicated how likely each team would be to win the game. Specifically, we asked participants to revisit each game and imagine that the two teams played that exact same game 100 times, meaning that each of those 100 games would have the same time, location, players, injuries, etc. as the actual game (see Appendix A2 for the exact wording of these instructions). Participants then reported

[13] In fact, across all 724 games in our dataset, we find no significant effects of predicting scores on winning team prediction accuracy. Thus, although we replicate Yoon et al.'s (2013) main result using a good measure of prediction quality, we do not replicate their result using the measure of prediction quality that they used.
[14] We report the results of our main analyses using accuracy as the dependent measure in Appendix A3.

how many games out of 100 they thought each team would win, and we converted these responses into probabilities of each team winning the actual game. These self-reported probabilities did not end up providing consistent evidence of participants' prediction processes, so we report their results in Appendix A2.

Reliance on Global vs. Local Information. In Experiments 1-16, we also collected Yoon and colleagues' (2013) measures of self-reported reliance on "global" and "local" information for making predictions, where "global information" refers to holistic, overall impressions of the teams, and "local information" refers to more nuanced information about specific aspects of the teams (e.g., their offensive capabilities). After participants made their predictions, we asked participants to "Please indicate the degree to which you considered each of these factors while making your predictions" and had them rate how much they considered three global factors ("overall impression of the two teams", "overall performance of the two teams in the past years", "overall performance of the two teams in recent years") and three local factors ("the teams' offensive abilities", "the teams' defensive abilities", "the teams' coaching abilities") on a scale from 1 ("not considered at all") to 7 ("seriously considered"). For experiments examining predictions about baseball games, we included an additional local factor ("the teams' pitching abilities") that was not included in, nor relevant for, Yoon et al.'s (2013) investigation of soccer matches. All global and local considerations were presented in randomized order. Following Yoon et al. (2013), we averaged participants' ratings of the three global factors into a single measure of "global considerations" ($\alpha = .68$) and the four local factors into a single measure of "local considerations" ($\alpha = .85$) so we could attempt to replicate their mediation analysis showing that people who predicted scores made worse winning team predictions because they considered global factors less. The results of these analyses are reported in detail in the Results section.

Sports Knowledge. We also collected information about participants' knowledge and familiarity with the sport league they made predictions about (e.g., Major League Baseball). In all 19 experiments, after participants made all of their predictions, we asked them eight questions designed to measure their knowledge and familiarity with the sport league. These questions were designed to vary in difficulty, and consisted of matching fairly well-known players to their teams, and matching teams to their division in the league. The instructions encouraged participants to leave the question blank rather than guess if they did not know the answer. The number of questions they answered correctly serves as our measure of participants' knowledge about the sport.[15] Participants' knowledge scores varied considerably (M = 4.58, SD = 2.91), with 12.6% of the sample answering no questions correctly and 23.7% of the sample answering all eight questions correctly.

Other Measures. Additionally, at the end of each experiment, we collected other exploratory measures (for example, prediction confidence and motivation). These additional measures ended up providing little insight into our investigation, so we report them and their results in Appendix A2. Finally, in all studies participants reported their

[15] In experiments 6-19, we also had participants self-report "How closely do you follow [sport league]?" and "How knowledgeable are you about [sport league]?" on scales from 1 ("not at all" / "not at all knowledgeable") to 7 ("extremely closely" / "extremely knowledgeable"). However, the percentage of wise predictions participants made was more strongly correlated with the number of knowledge questions they answered correctly ($r(10369) = 0.22$, $p < .001$) than it was with either their self-reported sports following or self-reported sports knowledge (both $rs(7783) = 0.15$, $ps < .001$), so we use their knowledge question scores as the main measure of knowledge in our analyses. The measured knowledge questions always came after the self-reported knowledge questions in all experiments that included both.

Mechanical Turk ID at the beginning of each experiment and their gender and age at the end of each experiment.

Table 1. Experiments 1-19: Percentage of participants making wise predictions in each prediction condition.

Experi-ment	Sport League	# of subjects	# of games	Winner Only	Score Only	Score + Winner	Relevant + Winner	Irrelevant + Winner
1	MLB	316	41	67.3%$_a$	61.4%$_b$	-	-	-
2	MLB	508	39	73.3%$_a$	67.4%$_b$	69.7%$_{ab}$	-	-
3	MLB	635	45	63.4%$_a$	57.5%$_b$	60.2%$_c$	-	-
4	MLB	631	45	70.8%$_a$	-	66.6%$_b$	66.8%$_b$	-
5	MLB	634	42	60.1%	-	58.8%	58.8%	60.2%
6	NHL	309	29	53.5%$_a$	-	49.8%$_b$	-	-
7	MLB	337	45	56.6%$_a$	-	53.9%$_b$	-	-
8	MLB	625	44	56.7%	-	55.7%	55.8%	-
9	MLB	422	41	60.9%	-	59.7%	-	-
10	MLB	728	45	59.3%	-	58.4%	58.5%	-
11	MLB	525	42	63.4%$_a$	-	61.8%$_b$	-	-
12	FIFA	622	48	61.2%$_a$	-	57.8%$_b$	-	-
13	NBA	420	32	70.3%	-	70.9%	-	-
14	NHL	541	32	70.0%	-	70.8%	-	-
15	NBA	775	32	74.1%	-	72.9%	72.4%	72.6%
16	NHL	711	30	73.3%	-	72.4%	71.4%	73.0%
17	NHL	811	31	74.8%$_a$	-	70.8%$_b$	-	75.2%$_a$
18	NBA	828	30	78.4%	-	76.5%	-	78.3%
19	NHL	518	31	69.7%$_a$	-	65.4%$_b$	-	-

Note. Each row shows the mean percentage of participants choosing the likely winners across games within each condition for that experiment. Within each row, means with different subscripts differ at $p < .05$ using within-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979). Experiment 3 manipulated whether the Score + Winner condition was paid based on the accuracy of their score prediction or their winner prediction; the Score + Winner column collapses across these two conditions. Experiments 4, 8, and 10 included two Relevant + Winner conditions, a condition in which participants first predicted total runs and a condition in which participants first predicted each team's hits; the Relevant + Winner column collapses across these two conditions. The relevant predictions made in Experiments 5, 15, and 16 were total runs scored, free throws attempted by each team, and saves made by each team, respectively. Experiments 17 and 18 included two Irrelevant + Winner conditions, a condition in which participants predicted the temperature outside the indoor stadium at the start of the game and a condition where participants predicted the high temperature in the game city on July 4th 2015 (about 6 months after the game); the Irrelevant + Winner column collapses across these two conditions. The irrelevant predictions made in Experiments 5, 15 and 16 were total game time, temperature outside the stadium at game time, and percentage of U.S. citizens in the crowd, respectively. FIFA = Fédération Internationale de Football Association; MLB = Major League Baseball; NBA = National Basketball Association; NHL = National Hockey League.

RESULTS

Most of our analyses analyze responses at the game level, examining for each game whether more participants made wise predictions when they were simply asked to select the winning team than when they were also (or instead) asked to make a detailed prediction. Using game as the level of analysis has the benefit of controlling for differences across games, while also allowing us to explore whether effects emerge for some games and not others. We could have instead analyzed these data at the participant level, examining the percentage of wise predictions each participant made, or at the prediction level, examining whether each individual prediction was wise or unwise. These alternative methods of analysis yield similar results and are reported in Appendix A3.

Does predicting scores make winner predictions worse?

We expected participants' winning team predictions to be worse when they were asked to predict final scores in addition to (or instead of) selecting winning teams. As shown in Table 1 and Figure 2, this expectation was confirmed. Participants in the Winner condition (M = 65.5%, SD = 25.3%) made wiser predictions than participants in the Score Only and Score + Winner conditions (M = 63.0%, SD = 23.9%), $t(708) = 11.92$, $p < .001$.[16,17] This is a small- to medium-sized effect: $d = .45$.[18] This pattern was observed in 17 of 19 experiments, it was statistically significant in 12 of them, and it was

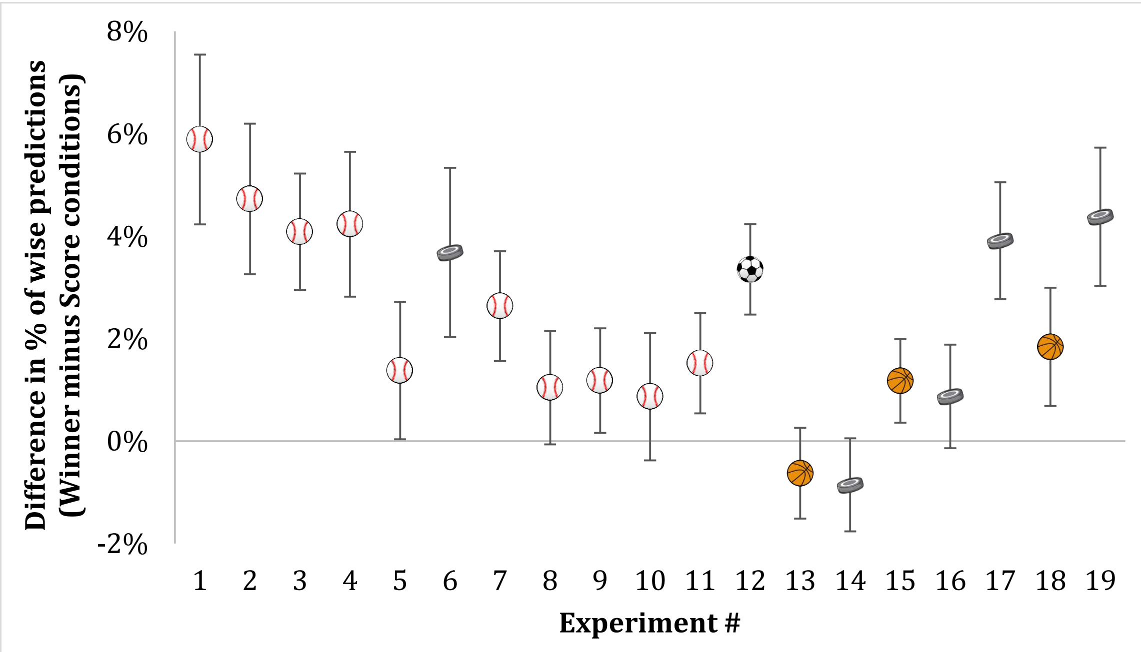
[16] For 15 of the 724 games in our sample, oddsmakers assigned an equal probability of winning to both teams, and so there was no "likely winner" for these games. Thus, data from these 15 games are excluded from all analyses that hinge on using betting market odds to identify a likely winner.

[17] For experiments containing both Score Only and Score + Winner conditions (Experiments 2 and 3), this analysis and the data reported in Figure 2 collapse these conditions into a single Score condition.

[18] For a paired-samples t-test, Cohen's d is computed by dividing the mean difference by the standard deviation of the difference. In this analysis, the standard deviation of the difference was 5.5% and so Cohen's d is (.655-.633)/.055 = .45.

in the expected direction for the majority of the games in our sample (68.1%), $X^2(1, N = 724) = 92.43$, $p < .001$.

Figure 2. Experiments 1-19: The difference in the percentage of wise predictions in the Winner vs. Score conditions.



Note. Errors bars indicate ±1 standard error adjusted to show within-subjects variation (Cousineau, 2005; Morey, 2008). Experiment 1's result compares the Winner to the Score Only condition, and the results from Experiment 2 and 3 compare the Winner condition to the average of the Score Only and Score + Winner conditions. The results of Experiments 4-19 compare the Winner condition to the Score + Winner condition.

Further analyses revealed that the negative effect of making score predictions was robust to variations across experiments and conditions. First, we observed the effect across sports. The Winner condition significantly outperformed the Score conditions in predictions of all sports except NBA basketball, for which the effect was marginal.[19] We

[19] Respectively, the separate t-tests for baseball, basketball, hockey, and soccer were: $t(421) = 9.45$, $p < .001$; $t(92) = 1.92$, $p = .058$; $t(146) = 5.74$, $p < .001$; $t(46) = 5.38$, $p < .001$.

also observed the effect across incentive structures. In Experiment 3, we manipulated whether the Score + Winner condition was incentivized for predicting the exact final score or for predicting the winner. It did not matter: The Winner condition significantly outperformed both, $ts(44) > 3.25$, p's $< .003$, and the two Score + Winner conditions did not differ from each other, $t(44) = 1.07$, $p = .29$. Finally, in Experiments 6 and 12, we did not give participants any team records as they made their predictions. This also did not matter: Participants in the Score + Winner condition still fared worse than participants in the Winner condition, $ts > 3.15$, $ps < .004$.

Does predicting other event details make predictions worse?

So far, we have seen evidence that predicting final scores makes winning team predictions worse. A final score prediction is a special type of detailed prediction in that it is a more detailed *version* of the winning team prediction, as one's final score prediction unambiguously reveals which team they think will win the game. Therefore, people who predict final scores presumably also have to think about which team will win the game as well as other information when making their predictions. However, if predicting final scores makes predictions worse because it increases the accessibility of information that is not useful for predicting the winner, then we would expect predictions about *any* relevant game details to have this effect. For example, asking participants to predict how many times each hockey team's goalie will block the opposing team from scoring might cause them to think more about the capabilities of the teams' goalies, and although this information might be useful in isolation, it would probably not provide diagnostic information over and above the teams' win/loss records since a goalie's ability directly affects how often his team wins.

In six of our experiments, we included conditions in which participants made detailed predictions about a different game outcome other than the final score before predicting the winner. For example, the number of hits each baseball team accumulates (Experiments 4, 8, and 10), the number of free throws each basketball team attempts (Experiment 15), or the number of saves each hockey team's goalie makes (Experiment 16) are relevant to the game because they influence the game's outcome. Similarly, the number of total runs in a baseball game (Experiments 4, 5, 8, and 10) is a relevant prediction because the game might unfold differently depending on whether the contest is low-scoring or high-scoring.[20]

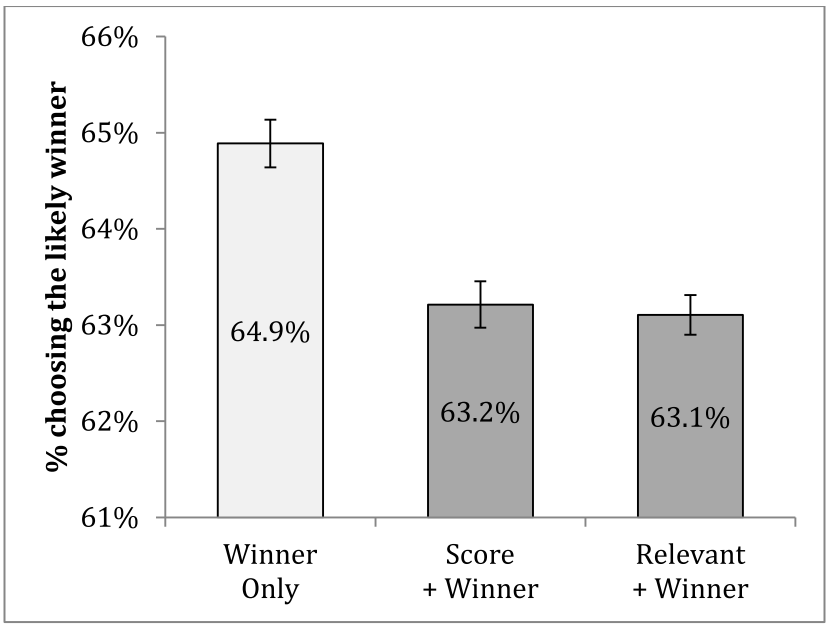
Across six experiments (*n* = 238 games), participants in conditions that predicted relevant details other than the score before predicting the winning teams predicted the likely winners to win less often (*M* = 63.1%, *SD* = 25.5%) than participants in conditions that only predicted winning teams (*M* = 64.9%, *SD* = 27.2%), $t(231) = 5.60$, $p < .001$.[21] This is a small-to-medium-sized effect: $d = .37$. We can also test whether predicting non-score relevant details worsens winner predictions as much as predicting the score does. The difference between the Score + Winner condition (*M* = 63.2%, *SD* = 25.2%) and conditions in which participants predicted non-score relevant details was not significant, $t(231) = 0.35$, $p = .72$. These analyses are consistent with the hypothesis that predicting

[20] Also, it is commonplace in sports betting for people to bet on whether the combined number of points scored by both teams will fall above or below a pre-specified total called the "over/under".

[21] Three of these experiments (4, 8, and 10) included two conditions asking participants to predict a relevant detail (other than the score) before predicting the winner. Specifically, in these experiments participants predicted either the number of hits each of two baseball teams would accrue (Hits + Winner condition) or the total number of runs that would be scored in the game (Runs + Winner condition). The analysis reported in the text averages across these two conditions. However, the results remain significant if we run the analyses using only the Runs + Winner condition from these three experiments, $t(231) = 5.70$, $p < .001$, or using only the Hits + Winner condition from these three experiments, , $t(231) = 4.39$, $p < .001$.

any relevant detail about an event will make predictions about more general outcomes worse. Next, we will focus on evaluating different possible explanations for *why* making detailed predictions makes predictions worse.

Figure 3. Experiments 4, 5, 8, 10, 15, and 16: The average percentage of participants making wise predictions in the Winner, Score + Winner, and Relevant + Winner conditions.



Note. Errors bars indicate ±1 standard error adjusted to show within-subjects variation (Cousineau, 2005; Morey, 2008).

Are predictions worse because people pay less attention?

So far, we have found that participants in the Winner condition, who are required to make simple categorical predictions (Winner condition), make better predictions than those in detailed conditions, who were additionally (or instead) required to make multiple, more difficult, free-entry predictions. It could be the case, then, that people who make detailed predictions make worse winning team predictions because they are more likely to become fatigued or confused, or are more likely to stop paying attention to the prediction task than participants in the Winner condition.

To investigate this, five of our experiments included conditions in which people were asked to predict an *irrelevant* detail before predicting the winning team. In our experiments, an "Irrelevant" detailed prediction is one that is unrelated to how the game will unfold. Importantly, while information about irrelevant details would be more accessible after making irrelevant detailed predictions, it should not feel sufficiently relevant to inform winning team predictions, and therefore should be omitted from consideration. In Experiment 5, participants in the Time + Winner condition predicted the duration of each baseball game in hours and minutes. In Experiment 16, participants in the Crowd + Winner condition predicted the percentage of fans in attendance who would be United States citizens for each game (many NHL hockey games attract non-American fans, especially those played in or near Canada). In Experiments 15 and 18 (basketball), and in Experiment 17 (hockey) participants in the Temperature + Winner condition predicted the outdoor temperature at the location and start time of each (indoor) game. Finally, Experiments 17 and 18 included an additional irrelevant detailed prediction in which participants predicted the high temperature in the game's location on July 4th, 2015 (approximately 6 months after the game).

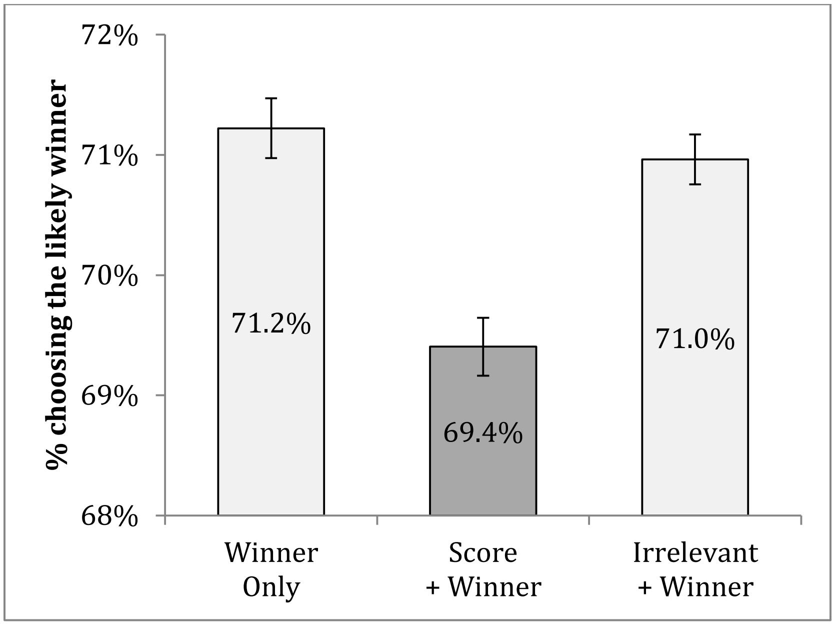
Like the participants who predicted scores and other relevant details about the game, participants who predicted irrelevant details made multiple, more difficult, free-entry predictions. Thus, if the fatigue or confusion that comes from making multiple detailed predictions is driving the effect, we should find that predictions are worse among those who predicted these irrelevant details as well.

However, this was not so. Across five experiments (*n* = 165 games), those who predicted an irrelevant event detail prior to predicting the winning team fared no worse (*M* = 71.0%, *SD* = 27.7%) than those who only predicted the winner (*M* = 71.2%, *SD* = 27.7%), $t(161) = 0.81$, $p = .42$. If this effect exists, we estimate it to be tiny: $d = .06$. Furthermore, this null effect can be put into context by the fact that participants who predicted irrelevant event details significantly outperformed participants who predicted final scores (*M* = 69.4%, *SD* = 26.2%), $t(161) = 3.64$, $p < .001$. This is a small- to medium-sized effect: $d = .29$.[22]

Thus, whereas predicting relevant details about the games resulted in winning team predictions that closely resembled those of the participants who predicted final scores, predicting irrelevant event details resulted in winning team predictions that closely resembled those of the participants who only predicted the winners. This suggests that the negative effect of making detailed predictions on winning team prediction quality is not due to increased levels of fatigue, confusion, or inattention, but rather because it makes them think differently about the event itself.

[22] Two of these experiments (17 and 18) included two conditions asking participants to predict a irrelevant detail before predicting the winner. Specifically, in these experiments participants predicted either the temperature outside the arena at the time and location of the game (Temperature + Winner condition) or the temperature in the game city on July 4th 2015 (July 4th + Winner condition). The analysis reported in the text averages across these two conditions. However, the results remain qualitatively identical if we run the analyses using only the Temperature + Winner condition from these two experiments (Winner vs. Irrelevant: $t(161) = 1.14$, $p = .26$; Score vs. Irrelevant: $t(161) = 3.44$, $p < .001$) or using only the July 4th + Winner condition from these two experiments (Winner vs. Irrelevant: $t(161) = 0.47$, $p = .64$; Score vs. Irrelevant: $t(161) = 3.67$, $p < .001$).

Figure 4. Experiments 5 and 15-18: The average percentage of participants making wise predictions in the Winner, Score + Winner, and Irrelevant + Winner conditions.



Note. Errors bars indicate ±1 standard error adjusted to show within-subjects variation (Cousineau, 2005; Morey, 2008)

Are predictions worse because people think harder?

Some researchers have claimed that conscious, deliberative thinking can sometimes lead to worse choices and predictions than unconscious, intuitive thinking (e.g., Dijksterhuis et al., 2006, and Dijksterhuis et al., 2009; however, the existence of this unconscious thought advantage has been challenged in a recent meta-analysis by Nieuwenstein et al., 2015). This raises the question of whether predicting scores makes winner predictions worse because predicting scores is more difficult and therefore causes people to think harder, as Yoon et al. (2013) interpreted their results to indicate.

To test whether thinking harder makes predictions worse, we ran three experiments (13, 14, 19; n = 95 games) in which we incentivized participants to think harder about some games than others. Again, participants were randomly assigned to only predict winning teams (Winner condition) or to predict final scores in addition to predicting winning teams (Score + Winner condition). Additionally, within-subjects, half of the games were assigned to either be worth either a smaller bonus (5 cents) or a much larger bonus (25 cents in Experiments 13 and 14, and 20 cents in Experiment 19—very large bonuses for a single question in a Mechanical Turk study). Which games were worth small and large bonuses was randomized between-subjects.[23]

We expected participants to think harder about the games that were worth a much larger bonus than usual. After making their predictions, participants reported "Overall, how carefully did you think about each game before making your winning team predictions?" and "Overall, how much effort did you invest in thinking about and making your predictions?" separately for the low- and high-incentive games.[24] Participants' ratings of thinking carefully about predictions and investing effort in making predictions were highly consistent (αs = .90 for both the low- and high-incentive games), so we averaged the two responses into a single measure of "thinking hard" about predictions. Participants reported thinking harder about the high-incentive games than the low-

[23] In Experiments 13 and 14, we first informed participants that they would be rewarded a 5-cent bonus each time they correctly predicted the winning team. After making sixteen predictions, they reported "Overall, how carefully did you think about each game before making your winning team predictions?" and "Overall, how much effort did you invest in thinking about and making your predictions?" We then informed them that the amount of the bonus had been increased to 25 cents per correct winning team prediction for a remaining block of games. They then made predictions about an additional sixteen games and rated how carefully they thought about and how much effort they invested in making predictions for just those sixteen 25-cent games. In Experiment 19, we informed participants at the outset that some games would be worth more than others. They then made all thirty low- and high-incentive predictions at once. The amount of the bonus (5 cents vs. 20 cents) was displayed prominently and alternated between games. After making all of their predictions, they rated how carefully they thought about and how much effort they invested in making their predictions separately for the 5-cent games and the 20-cent games.

[24] This wording is taken from Experiment 13 and 14. The wording of these questions was slightly different in Experiment 19, and is reported Appendix A2.

incentive games in both the Winner condition (*M* = 5.80, *SD* = 1.16 vs. *M* = 5.44, *SD* = 1.25, *t*(748) = 13.36, *p* < .001) and Score + Winner condition (*M* = 5.85, *SD* = 1.14 vs. *M* = 5.50, *SD* = 1.22, *t*(685) = 12.56, *p* < .001). However, participants in the Score + Winner condition did not report thinking significantly harder about either low- or high-incentive games than participants in the Winner condition (*t*s < 0.91, *p*s > .36).

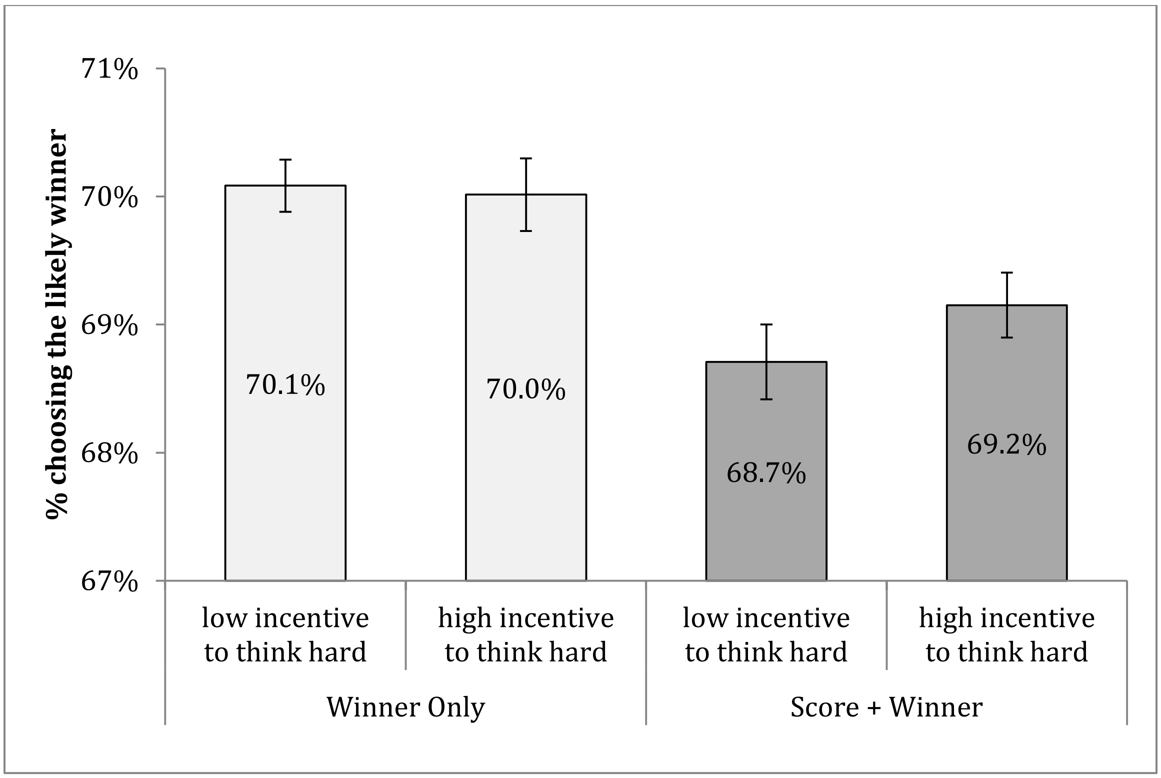
If predicting scores worsens predictions because it makes people think harder, then making people think harder should decrease the quality of their predictions, especially among those in the Winner condition, who were presumably not thinking as hard as participants in the Score + Winner condition before. This was not the case. Participants in the Winner condition did not make significantly worse predictions when the stakes were higher (*M* = 70.0%, *SD* = 17.4%) than when they were lower (*M* = 70.1%, *SD* = 16.8%), *t*(94) = 0.23, *p* = .82, and participants in the Score + Winner condition made directionally *wiser* predictions when the stakes were higher (*M* = 69.2%, *SD* = 17.2%) than when they were lower (*M* = 68.7%, *SD* = 15.8%), *t*(94) = 1.21, *p* = .23. Furthermore, regardless of incentive, participants who reported thinking harder actually made a *greater* percentage of wise predictions, *b* = 0.87%, *t*(2889) = 3.73, *p* < .001.[25, 26] Finally, as usual, participants in the Winner condition made wiser predictions than participants in the Score + Winner condition for both low- and high-incentive games, *ts* > 2.25, *ps* < .027. These

[25] Analysis includes fixed effects for experiment.

[26] Dijksterhuis et al. (2009) found that the unconscious thought advantage was moderated by "expertise" as defined by above-median self-reported knowledge, such that only experts derived an advantage from unconscious thinking when they made predictions about soccer game outcomes. However, we found no such moderation of self-reported knowledge on the effect of thinking hard on average prediction quality, *b* = -0.19%, *t*(2798) = -1.27, *p* = .17. Furthermore, amongst the 124 participants who reported the highest level of sports knowledge, thinking hard was marginally positively correlated with making a greater percentage of wise low- and high-incentive predictions, *r*(246) = 0.11, *p* < .10.

results suggest that thinking hard about predictions does not explain why people who make detailed predictions make worse winning team predictions.

Figure 5. Experiments 13, 14, and 19: The average percentage of participants making wise predictions in the Winner and Score + Winner conditions for low- versus high-incentives.



Note. Errors bars indicate ±1 standard error adjusted to show within-subjects variation (Cousineau, 2005; Morey, 2008)

Are predictions worse because people think less globally or more locally?

In a previous investigation of why predicting scores makes winning team predictions worse, Yoon et al. (2013) found that predicting scores made people think about global information marginally less, and this marginally mediated the relationship between predicting scores and prediction accuracy. We did not replicate these results. Across 16 experiments (experiments 1-16, n = 6,541 participants) we found that predicting scores had no effect on self-rated reliance on global considerations, $b = -0.006$, $t(6525) = 0.19$, $p = .85$. We did find that that predicting the score had a very small but marginally positive effect on ratings of local considerations, $b = 0.071$, $t(6525) = 1.83$, $p = .067$, and that an increase in local considerations had a small but significant effect on the percentage of wise predictions made, $b = 0.206\%$, $t(6525) = 2.53$, $p = .012$. However, a bootstrap mediation analysis (Preacher & Kelley, 2011) revealed that this increase in local considerations did not even partially mediate the effect of predicting the score on winning team prediction quality, $b_{indirect\ effect} = 1.57 \times 10^{-4}$, 95% CI = [$-1.78 \times 10^{-5}$, 4.04×10^{-4}]. Thus, we believe it is unlikely that detailed predictions make predictions worse because they cause people to consider global factors less or local factors more.

Do people who make detailed predictions use useful information less?

Although our data do not reveal exactly what information participants were thinking about when making their predictions, we can examine how participants used the information that we gave them. Each experiment (with the exception of Experiments 6 and 12) gave participants at least two pieces of information: win/loss records and home team status. Both win/loss records and home field advantage are diagnostic for determining how likely a team is to win a game, and together these variables account for 66% of the variation in the probabilities set by Vegas oddsmakers for the games in our dataset.

We used logistic regressions to estimate how much a team's win/loss record and home team status influenced each participant's likelihood of predicting the team to win the game.[27] Specifically, for each participant in each experiment, we estimated the probability they would predict the team to win the game based on whether or not that team had the better record (specifically, whether they had won a greater percentage of games than their opponent) and whether or not that team was the home team.[28] Additionally, we expected that people's use of win/loss records and home field advantage would depend on how competitive the game was. We defined a maximally competitive game as one in which the teams have near-identical win/loss records (indicating they are evenly matched), and a non-competitive game as one in which one team has a much better win/loss record than the other (indicating they are very unevenly matched). Our measure for the competitiveness of the game was the absolute difference between the two teams' Win Percentages, for which values ranged from 0 (the teams had identical Win Percentages) to 1 (one team had won every game and the other team had lost every game). We predicted that as games became less competitive (i.e., as the disparity between the teams' win/loss records became more extreme), people would rely more on which team had the better record and less on home field advantage for making predictions. Thus, we interacted dummies for whether the team had the better record and whether the team was the home team with how competitive the game was:

[27] These analyses do not include Experiments 6 and 12 because we did not provide win/loss record information for these experiments.

[28] Since we are analyzing how characteristics of teams affect participants' likelihood of predicting them to win, the data were recoded so that each team was a separate observation with whether the team was predicted to win as the dichotomous dependent variable and home team status and the teams' record information as predictor variables. This means that each prediction generated two observations: one for the chosen team and one for the unchosen team. To adjust for the fact that these team pairs contribute the same information, we clustered standard errors by participant-game.

$$logit(predicted\ the\ team\ to\ win) = \beta_0 + \beta_1\, better\ record + \beta_2\, home\ team + \beta_3\, better\ record * |record\ difference| + \beta_4\, home\ team * |record\ difference|$$

Once we estimated the weights given to team records and home field advantage for each participant in each experiment, we analyzed how detailed predictions affected information use by comparing these weights between participants in different prediction conditions.

Table 2 reports the marginal effects of having the better record, being the home team, and the competitiveness of the game on the likelihood of predicting a team to win for participants in the Winner condition. When games were maximally competitive (i.e., when teams had near-identical Win Percentages),[29] participants in the Winner condition were 17.0% more likely on average to predict the team to win when it had the better record than when its opponent had the better record, and 13.6% more likely on average to predict the team to win when it was the home team than when it was the visiting team. We can also see how the use of this information changes as games become less competitive. As expected, we find that people relied on whether the team had the better record more and whether the team was the home team less as the disparity between the teams' records increased.

[29] The twelve games where the two teams had identical Win Percentages were dropped from this analysis because neither team had the better win/loss record.

Table 2. Experiments 1-5, 7-11, and 13-19: How much weight participants in the Winner condition gave to win/loss records and home field advantage when making predictions.

Coefficients	**Winner**
better record	0.170 ***
home team	0.136 ***
| record difference |	-3.302 ***
better record * | record difference |	2.522 ***
home team * | record difference |	-1.172 ***

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

Next we examine how participants' use of win/loss records and home field advantage differed between prediction conditions. However, because the various types of detailed predictions spanned different experiments and therefore different sets of games, we cannot directly compare the coefficients for information use in the detailed prediction conditions to the coefficients in Table 2, because they would be estimated from different populations. For this reason, Table 3 reports the *differences* in information use from the Winner condition for each type of detailed prediction conditions (Score, Relevant, and Irrelevant) in the experiments that include both. By using the Winner condition as a benchmark in each set of games (i.e., games with Score conditions, games with Relevant conditions, games with Irrelevant conditions), we can see how participants' use of team records and home field advantage changed based on the type of detailed predictions they made.

In Table 3, a positive coefficient indicates that participants who made detailed predictions gave that information *more* weight than participants in the Winner condition, and a negative coefficient indicates that they gave that information *less* weight. Figure 6 similarly displays the marginal effects of having the better record and being the home team on the likelihood of predicting the team to win separately for the Winner and detailed prediction conditions for each set of games.

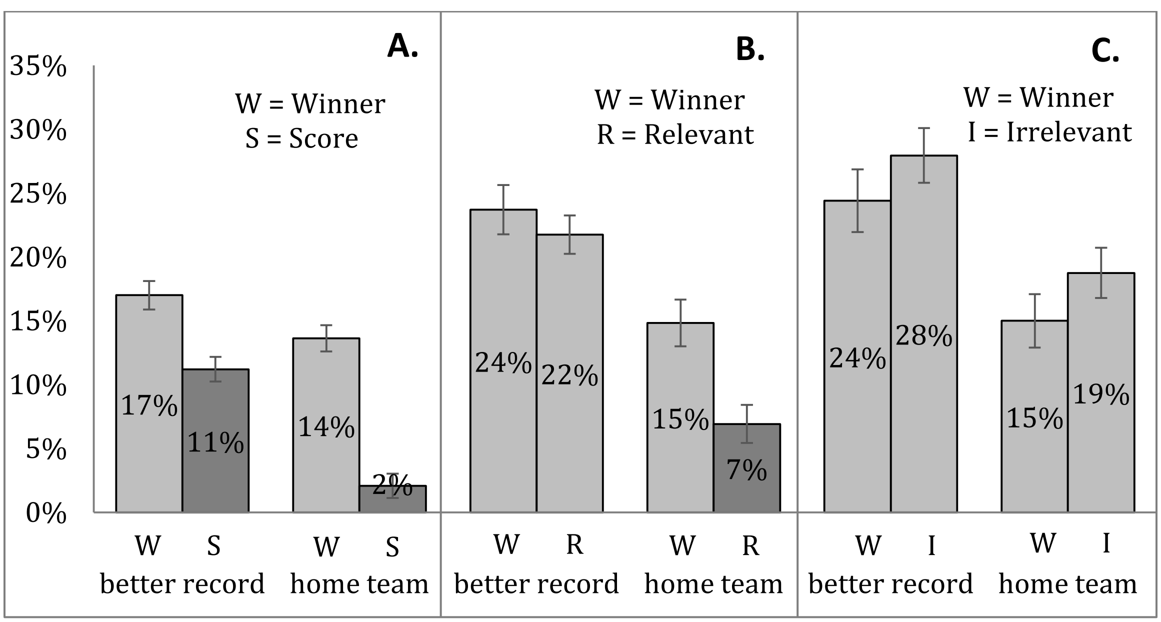
Table 3 and Figure 6 reveal that participants who predicted scores gave significantly less weight to both which team had the better record and which team was playing at home than participants in the Winner condition, and participants who predicted other relevant details gave directionally less weight to which team had the better record and significantly less weight to which team was playing at home. Furthermore, these decreases in weight were greater for home field advantage than for having the better record. Interestingly, the people who predicted irrelevant details gave these two cues directionally *more* weight than people in the Winner condition; however, these differences were not significant. These results show that people who made relevant detailed predictions (including final scores) gave less weight to important diagnostic information than people who only predicted winning teams. This is the pattern we would expect if people who make relevant detailed predictions consider less important information while making winning team predictions.

Table 3. Experiments 1-5, 7-11, and 13-19: Differences in information weights from the Winner condition in the detailed prediction conditions.

Coefficients	**Score**	**Relevant**	**Irrelevant**
better record	-0.058 ***	-0.020	0.035
home team	-0.116 ***	-0.079 ***	0.037
| record difference |	0.149	0.237	-0.033
better record * | record difference |	-0.677 **	-0.513	-0.419
home team * | record difference |	0.381 ***	0.036	0.448
Number of participants in sample	5,537	1,958	1,541
Number of games in sample	644	235	162

Note. * *p* < .05, ** *p* < .01, *** *p* < .001.

Figure 6. Experiments 1-5, 7-11, and 13-19: The increase in the likelihood of predicting a team to win when it had the better record and when it was the home team for Winner vs. Score conditions (A), Winner vs. Relevant detailed conditions (B), and Winner vs. Irrelevant detailed.



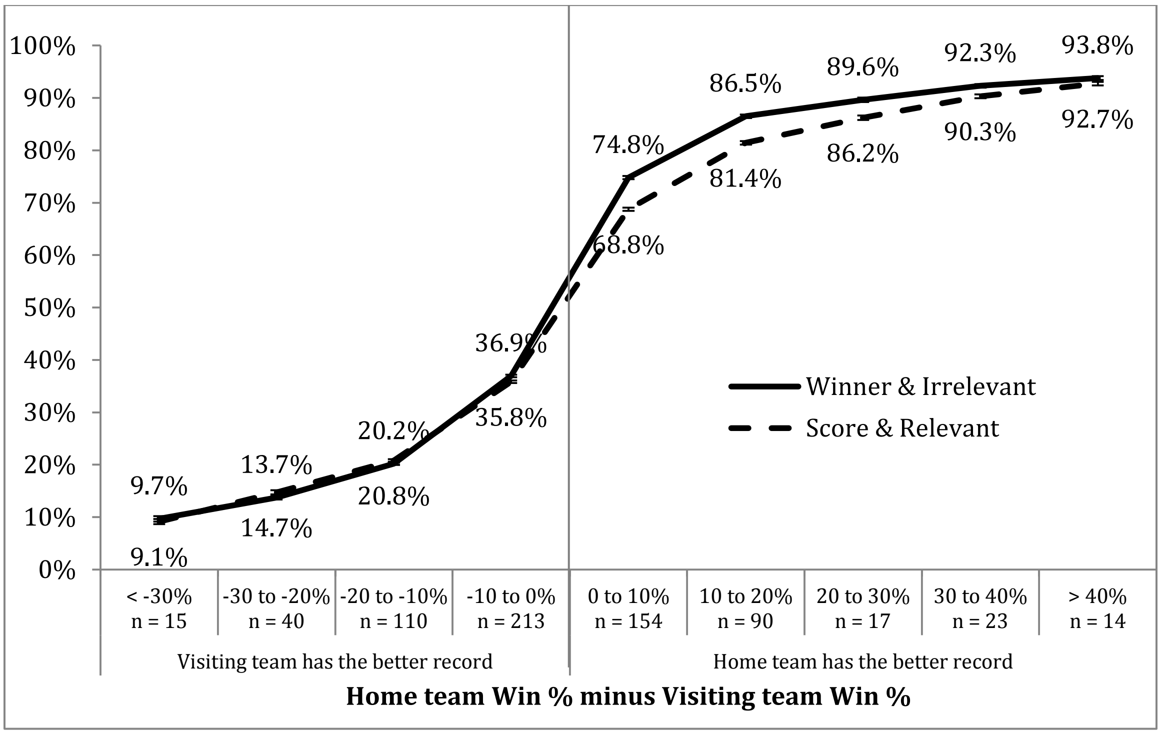
Note. Errors bars indicate ±1 standard error of the interaction between information use and prediction condition (Winner vs. detailed). The coefficients for chart A only include games that had final score prediction conditions (*n* = 644 games), the coefficients for chart B only include games that had non-score relevant prediction conditions (*n* = 235 games), and the coefficients for chart C only include games that had irrelevant prediction conditions (*n* = 162 games).

Which games will show the effect?

If detailed predictions cause people to give less weight to the teams' win/loss records and home team status, then detailed predictions might not *always* make predictions worse. Consider two different types of games in our sample. In some games, the home team had the better record, meaning that both of the cues that people rely on to predict the winner (win/loss records and home field advantage) indicate that the home team is more likely to win. Since making detailed predictions causes people to give less weight to both of these cues, the difference in prediction quality between the non-detailed and relevant-detailed conditions should be most pronounced for these games. The right-hand side of Figure 7 shows this to be the case: When the home team had the better record, people who predicted relevant details about the game were considerably less likely to predict the home team to win.

Now consider a different type of game: one for which the *visiting team* had the better record. For these games, the cues that people rely on to predict the winner point in opposite directions: choosing the team with the better record would result in predicting the visiting team, whereas choosing the team that with the home field advantage would result in predicting the team with the inferior record. Since making detailed predictions causes people to be less likely to predict the team with the better record but *more* likely to predict the visiting team (since they largely ignore home field advantage), the difference between the non-detailed and detailed conditions might not emerge for these games. The left-hand side of Figure 7 shows this to be the case: When the visiting team had the better record, people who predicted relevant game details did *not* predict any differently those whose who only predicted winners.

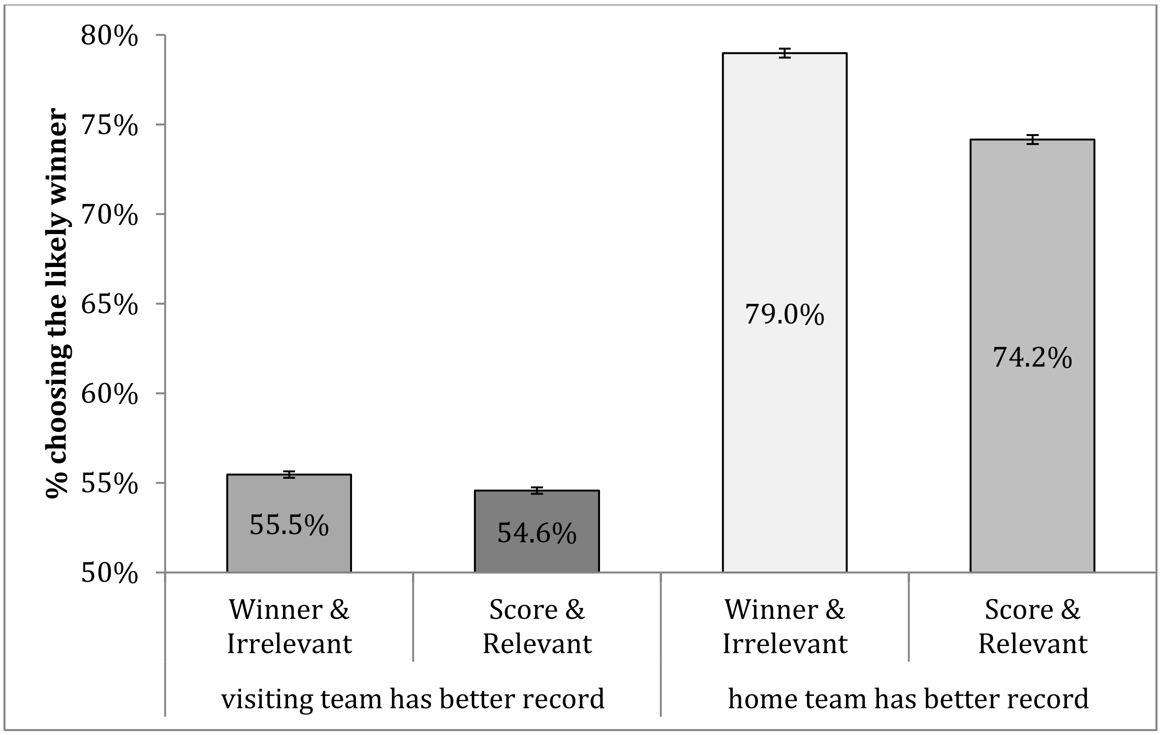
Figure 7. Experiments 1-5, 7-11, and 13-19: The percentage of participants predicting that the home team would win by prediction condition and difference in win/loss records.



Note. Errors bars indicate ±1 standard error adjusted to show within-subjects variation (Cousineau, 2005; Morey, 2008).

Similarly, we can examine the effect that the consistency of the two cues has on the propensity to make wise predictions. The right side of Figure 8 illustrates that when the information we give them is diagnostically consistent (the home team also has the better record), people who predict relevant game details make considerably less wise predictions than people who only predict winners (*M* = -4.8%, $t(295) = 13.64$, $p < .001$), but when the information we give them is inconsistent (the home team has the inferior record), this difference is much smaller (*M* = -0.9%, $t(354) = 3.60$, $p < .001$).

Figure 8. Experiments 1-19: The percentage of participants making wise predictions by whether the home team also had the better record.



Note. Errors bars indicate ±1 standard error adjusted to show within-subjects variation (Cousineau, 2005; Morey, 2008).

Thus, by understanding the process by which detailed predictions affect prediction quality, we can predict when the effect will emerge and when it will not. In this context, it will emerge when giving less weight to both the teams' records and home field advantage will alter predictions (as when the home teams have better records) but not when giving less weight to both of these cues will not (as when the visiting teams have better records).

This finding is important because it allows us to predict how this effect will play out in other prediction contexts. To predict when the effect will emerge, it will be important to first identify which cues are given less weight by people making detailed predictions. Then, one needs to consider how giving that cue less weight would affect the wisdom of predictions. When the available information offers conflicting diagnoses, giving all cues less weight might not actually alter the quality of those predictions, and so making detailed predictions might have no effect on the quality of other predictions. Moreover, if these cues are normally *over*weighted rather than underweighted, then making detailed predictions may actually *improve* prediction quality.

GENERAL DISCUSSION

In this paper, we investigated whether and why making detailed predictions about an event makes predictions of other outcomes worse. We found that asking participants to make predictions about any relevant detail in sports games resulted in worse winning team predictions. We also largely ruled out the possibility that this effect could be explained by inattention or fatigue, thinking too hard, or thinking about global impressions of the teams less. Rather, our data suggest that making detailed predictions makes other similar predictions worse by influencing what information forecasters did (and did not) incorporate into their predictions. We further found that detailed predictions only negatively affected games for which there was consistent diagnostic information—namely, games for which the home team also had the better record.

We already knew from past research that the information given to forecasters affects the quality of their predictions; however, to the best of our knowledge it was unknown whether asking forecasters to make additional similar predictions could also affect prediction quality. We believe that this happens because having people predict the details of an event makes them think about additional information that is unimportant for predicting other related outcomes; however, once this information is made accessible in memory, people are more likely to use it in their forecasts, decreasing the weight given to more important information. This suggests that a relatively simple way to improve predictions could be to take a top-down approach and start by first predicting the most general outcomes and then letting those forecasts guide predictions of more detailed outcomes. Importantly, this prescription is not intuitive, as most decision-makers feel compelled to try to think through all of the available details about an event before making their forecasts (Lovallo & Kahneman, 2003).

Our results also reveal that a negative effect of making detailed predictions on subsequent related predictions is not universal. Because participants who predicted game details used both home team status and record advantage less, we only found a sizeable detrimental effect when both pieces of information favored the same team (i.e., the home team had the better record), in which case the effect of the reduction in the use of the two cues was compounded, and the effect was largely eliminated when each piece of information favored a different team (i.e., the visiting team had the better record), in which case the effect of the reduction of the use of the two cues partially canceled out.

In fact, if predicting additional details about an event decreases the weight placed on heavily weighted cues, then we can imagine cases where making detailed predictions could actually make subsequent predictions *better*. In our experiments, participants generally had a good sense that having the better record and being the home team were predictive of winning the game, and that, for most games, having the better record is more important than being the home team. However, what about circumstances where people do not have good intuitions about what information is important? For example, someone who wants to forecast demand for a novel piece of wearable technology might believe that computing capability is more important to consumers than stylishness, when in fact the reverse might be true. In this case, having the forecaster make additional detailed predictions (e.g., which of the product's features will be most attractive?) might inadvertently make his forecasts better because doing so would reduce the weight given to an over-weighted attribute. This example emphasizes the importance of understanding how forecasters are already using the information available to them in order to understand how making additional detailed predictions would affect their other predictions.

Another point of concern moving forward is that it is not clear how people integrate conflicting information when making predictions in this context, and it is also not clear how predicting other details would affect how forecasters combine conflicting cues. Past research on how people use conflicting information is mixed, with some finding that the less important of the conflicting cues is largely ignored (Keeley & Doherty, 1972; Mertz & Doherty, 1974; Slovic, 1966; Yaniv, 2004), others saying that people are able to integrate the inconsistent cues in a roughly linear fashion (Lichtenstein et al., 1975; York, Doherty, & Kamouri, 1987), and others still saying that whether the inconsistent information is disregarded or integrated varies based on other attributes, such as task predictability (Brehmer, 1972). The fact that the differences between detailed and non-detailed prediction conditions is smaller for games with conflicting cues is consistent with both omission and linear combination models of conflicting cue use. Overall, this suggests that identifying forecasters' intuitive weights and methods for combining conflicting information in the specific prediction context being examined would likely be a necessary precursor for predicting whether making detailed predictions would make other predictions worse.

APPENDIX A1: EXPERIMENTAL INSTRUCTION AND DESIGNS

All experiments had similar designs. In the interest of clarity and brevity, we first present an example of a prototypical experiment. Then, we will present the details of each individual experiment in terms of the predictions that were made, the different experimental conditions, and how they differed from the prototypical design. Any questions about the instructions, stimuli, or survey designs should be directed to Theresa Kelly.

Example Experiment

In the example below, each image represents a separate page in the survey. The images used in the example are taken from Experiment 8.

Figure A1 1. Example Experiment: Informed consent.

We are researchers at the University of Pennsylvania and we are investigating your predictions of Major League Baseball games. In this survey, you will answer questions about baseball, as well as provide demographic and contact information. Please be assured that your responses will be kept completely confidential.

The survey will take you approximately 10 to 15 minutes to complete, and you will be compensated $0.50 by MTurk for your participation. You will also have the chance to earn bonus payment based on performance.

Your participation in this research is voluntary. You have the right to withdraw at any point during the study, for any reason, and without prejudice.

By clicking the forward button (>>), you acknowledge that your participation in the study is voluntary and that you are aware that you may choose to terminate your participation in the study at any time and for any reason without penalty.

Please enter your MTurk ID in the box below. **It is essential for us to have your MTurk ID to credit any bonuses you earn to your MTurk account. If you do not enter your correct MTurk ID, you will not receive bonus payment.**

>>

Figure A1 2. Example Experiment: Winner condition instructions.

In this section, you will predict the outcomes of the **44 Major League Baseball games** scheduled to be played from Monday May 5th through Wednesday May 7th.

Specifically, you will predict the **winning team** for each game.

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Figure A1 3. Example Experiment: Winner condition predictions.

This is the list of the 13 Major League Baseball games scheduled to be played Monday May 5th.

Each game displays the visiting team (listed first) and the home team (listed second). We also give you the Win/Loss records and probable pitchers for each team. All information is up to date as of 8:00am EST today, Monday May 5th.

For each game, please predict the **winning team.**

Each time you correctly predict the winning team, you will earn $0.05.

Monday May 5th, 2014 at 7:05 pm

Minnesota Twins @ Cleveland Indians

Team	Wins	Losses	Probable Pitcher
Minnesota Twins	14	15	Kyle Gibson
Cleveland Indians	13	18	Zach McAllister

If you correctly predict the winner of this game, you will earn $0.05

Who will win this game?

Minnesota Twins Cleveland Indians

Note. The game shown in the example above was followed by the other 12 games scheduled to be played that same day displayed one after the other on the same page. After the first page of games, the next page followed the exact same format, including the instructions at the top of the page, but for all of the games for the next day. This repeated for as many days as were included in the experiment. In this example, there were three days of games and therefore three pages of predictions.

Figure A1 4. Example Experiment: Score + Winner condition instructions.

In this section, you will predict the outcomes of the **44 Major League Baseball games** scheduled to be played from Monday May 5th through Wednesday May 7th.

Specifically, you will predict the **final score** and the **winning team** for each game.

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Figure A1 5. Example Experiment: Score + Winner predictions.

This is the list of the 13 Major League Baseball games scheduled to be played Monday May 5th.

Each game displays the visiting team (listed first) and the home team (listed second). We also give you the Win/Loss records and probable pitchers for each team. All information is up to date as of 8:00am EST today, Monday May 5th.

For each game, please predict the **final score** and the **winning team.**

Each time you correctly predict the winning team, you will earn $0.05.

Monday May 5th, 2014 at 7:05 pm

Minnesota Twins @ Cleveland Indians

Team	Wins	Losses	Probable Pitcher
Minnesota Twins	14	15	Kyle Gibson
Cleveland Indians	13	18	Zach McAllister

If you correctly predict the winner of this game, you will earn $0.05

What will the final score of this game be?

How many runs will the **Minnesota Twins** score?

How many runs will the **Cleveland Indians** score?

Who will win this game?

Minnesota Twins

Cleveland Indians

Note. Participants were restricted from entering tied scores. The game shown in the example above was followed by the other 12 games scheduled to be played that same day displayed one after the other on the same page. After the first page of games, the next page followed the exact same format, including the instructions at the top of the page, but for all of the games for the next day. This repeated for as many days as were included in the experiment. In this example, there were three days of games and therefore three pages of predictions.

Figure A1 6. Example Experiment: Prediction strategy.

Briefly describe what strategies you used to make your predictions:

Note. Participants were required to enter a minimum of 25 characters.

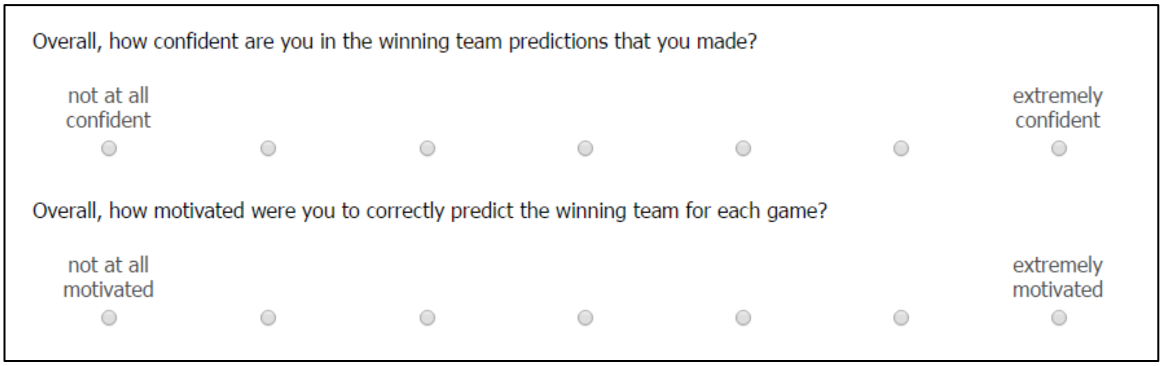
Figure A1 7. Example Experiment: "Global" and "local" considerations.

Please indicate the degree to which you considered each of these factors while making your predictions:

	not considered at all						seriously considered
overall impression of the two teams							
overall performance of the two teams in the past years							
overall performance of the two teams in recent years							
the teams' offensive abilities							
the teams' defensive abilities							
the teams' pitching abilities							
the teams' coaching abilities							

Note. The order of items was randomized between participants. The item "the teams' pitching abilities" only appeared for Major League Baseball games and was omitted for all experiments using other sports.

Figure A1 8. Example Experiment: Winner condition confidence and motivation.


Overall, how confident are you in the winning team predictions that you made?

not at all confident

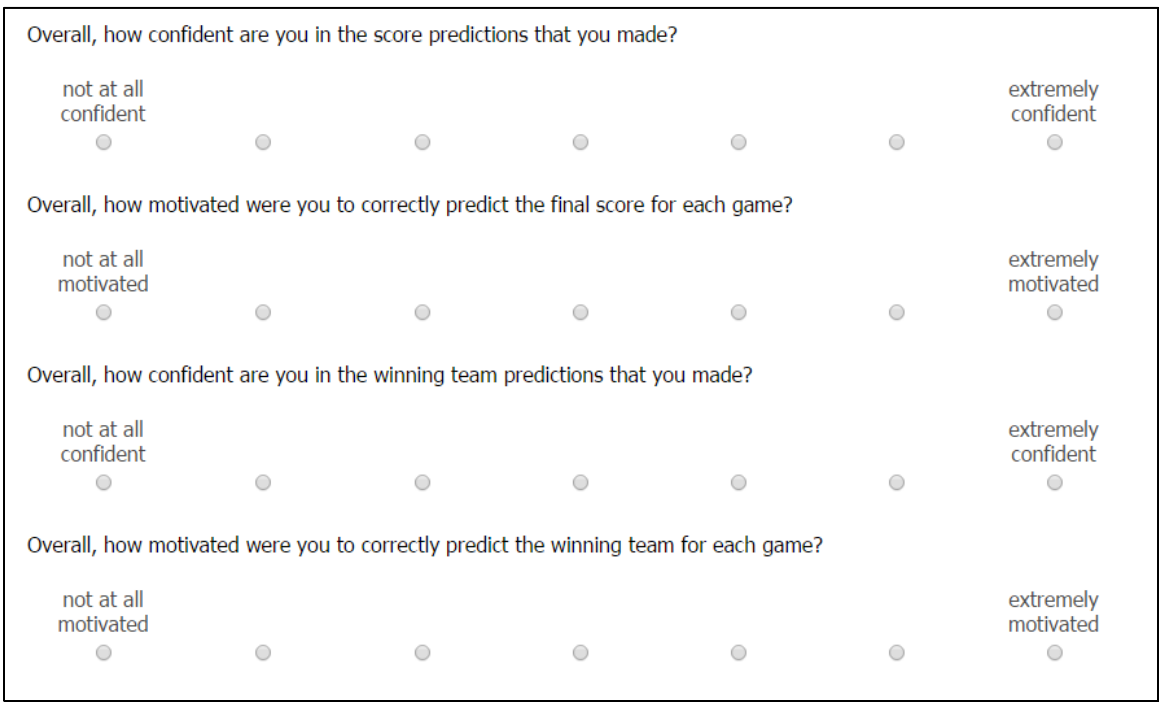
extremely confident

Overall, how motivated were you to correctly predict the winning team for each game?

not at all motivated

extremely motivated

Figure A1 9. Example Experiment: Score + Winner condition confidence and motivation.


Overall, how confident are you in the score predictions that you made?

not at all confident

extremely confident

Overall, how motivated were you to correctly predict the final score for each game?

not at all motivated

extremely motivated

Overall, how confident are you in the winning team predictions that you made?

not at all confident

extremely confident

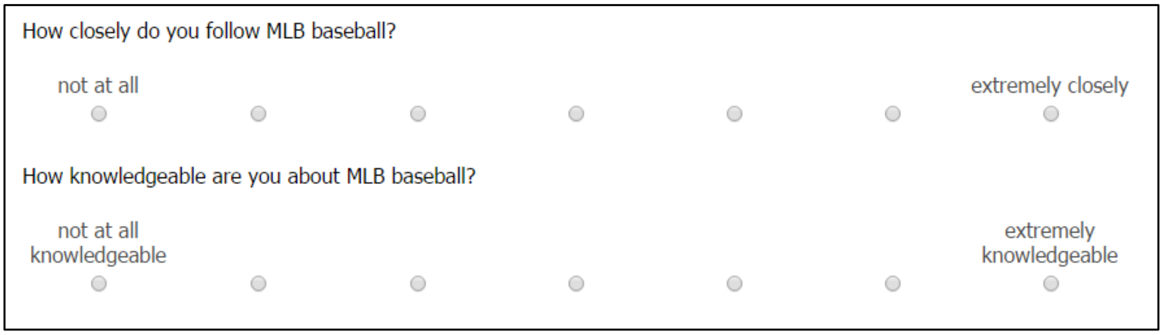
Overall, how motivated were you to correctly predict the winning team for each game?

not at all motivated

extremely motivated

Note. See the "additional measures" section of the Supplement for the exact wording of the confidence and motivation questions for predictions other than the winning team and final score.

Figure A1 10. Example Experiment: Self-reported following and knowledge.



How closely do you follow MLB baseball?

not at all ... extremely closely

How knowledgeable are you about MLB baseball?

not at all knowledgeable ... extremely knowledgeable

Figure A1 11. Example Experiment: Measured knowledge.

In this section, we will ask you 8 questions designed to assess your baseball knowledge.

Please answer each of the following questions to the best of your ability.

Please do NOT look up the answers while completing this section. It is important for us to have an accurate sense of your baseball knowledge. **Your bonus payment will <u>not</u> be affected by how you answer these questions.**

If you do not know an answer, please leave it blank and move on to the next question.

In which division do the St. Louis Cardinals play?

Which MLB team does Clayton Kershaw play for?

Which MLB team does Yu Darvish play for?

Which MLB team does Evan Longoria play for?

Which MLB team does Andrew McCutchen play for?

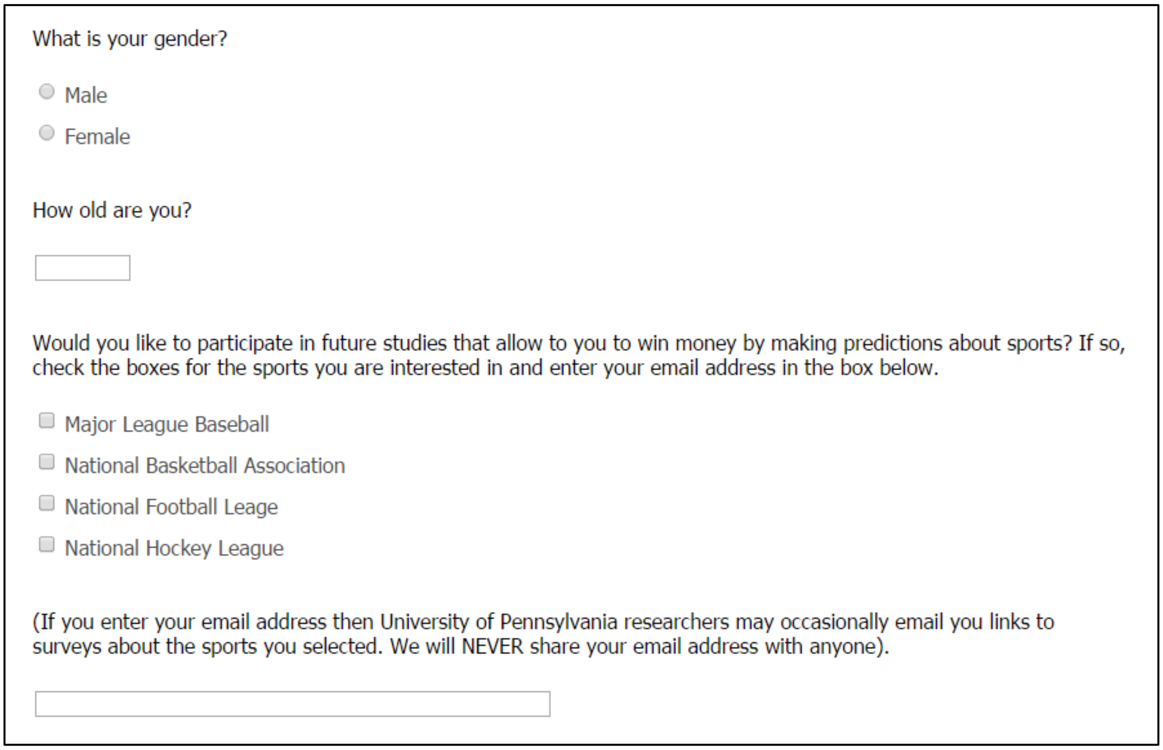
In which division do the Minnesota Twins play?

Which MLB team does Homer Bailey play for?

Which MLB team does Cliff Lee play for?

Note. The order of questions was randomized between participants. Players and teams used varied between experiments. Participants were not required to answer any of these questions.

Figure A1 12. Example Experiment: Gender, age, and contact.



What is your gender?

Male

Female

How old are you?

Would you like to participate in future studies that allow to you to win money by making predictions about sports? If so, check the boxes for the sports you are interested in and enter your email address in the box below.

Major League Baseball

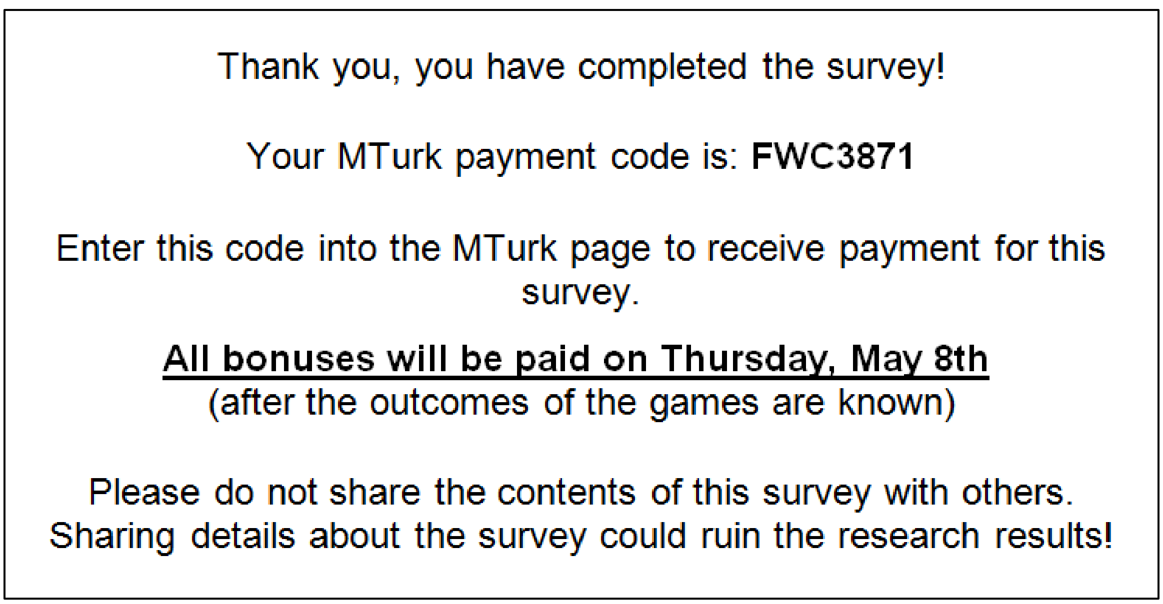
National Basketball Association

National Football Leage

National Hockey League

(If you enter your email address then University of Pennsylvania researchers may occasionally email you links to surveys about the sports you selected. We will NEVER share your email address with anyone).

Figure A1 13. Example Experiment: Survey completion.



Thank you, you have completed the survey!

Your MTurk payment code is: **FWC3871**

Enter this code into the MTurk page to receive payment for this survey.

All bonuses will be paid on Thursday, May 8th
(after the outcomes of the games are known)

Please do not share the contents of this survey with others.
Sharing details about the survey could ruin the research results!

Individual Experiments

Each experiment is accompanied by a Experiment Design Table that provides information about the number and types of predictions in the experiment, the different conditions, what record information was given, and ways that the experiment deviated from the Example Experiment in the previous section.

For each experiment, we also give one example of the predictions made in each condition. The separate instructions page for a new condition is only given for first experiment that that condition appears in (e.g., the Hits + Winner condition appears in Experiments 4, 8, and 10, but we only give the instructions in the description of Experiment 4).

All the games for a single day were displayed on a single page with the exception of Experiments 13, 14, and 17-19. Descriptions of how the display format of the predictions for these experiments are explained in their respective Experiment Design Tables.

The experiments in this section do NOT repeat all of the measures collected. However, any additional measures that differed from the Example Experiment are described in the Experiment Design Table. To see what these individual measures look like, refer to the "Additional Measures" supplement.

Experiment 1

Table A1 1. Experiment 1 design.

Predictions	41 Major League Baseball games played on June 4th (15 games), June 5th (15 games), and June 6th (11 games) in 2013.
Run Date	June 3rd, 2013
Conditions	Winner, Score Only
Record information	Wins, losses, probable pitchers
Measures in the example that are NOT included in this experiment	· Prediction strategy · Motivation and confidence · Self-reported following and knowledge · Which sports they are interested in being contacted about.
Measures NOT in the example that ARE included in this experiment	· Maximizing Tendency Scale (included for an unrelated study).
Other deviations from the example format	· The Winner condition was incentivized 5 cents for correctly predicting the winner and the Score Only condition was incentivized 40 cents for correctly predicting the exact final score. · Participants were not reminded of the payoff amounts for each game (e.g. "If you correctly predict the winner of this game, you will earn $0.05").

Figure A1 14. Experiment 1: Winner condition predictions.

This is the list of games due to be played on Tuesday, June 4th.

Each game displays the visiting team (listed first), the home team (listed second), their win-loss records, and the probable starting pitchers for that game.

The win-loss records for each team are as of Monday morning, June 3rd.

For each game, please predict which team will win.

Tuesday, June 4th, 2013 @ 7:05 pm

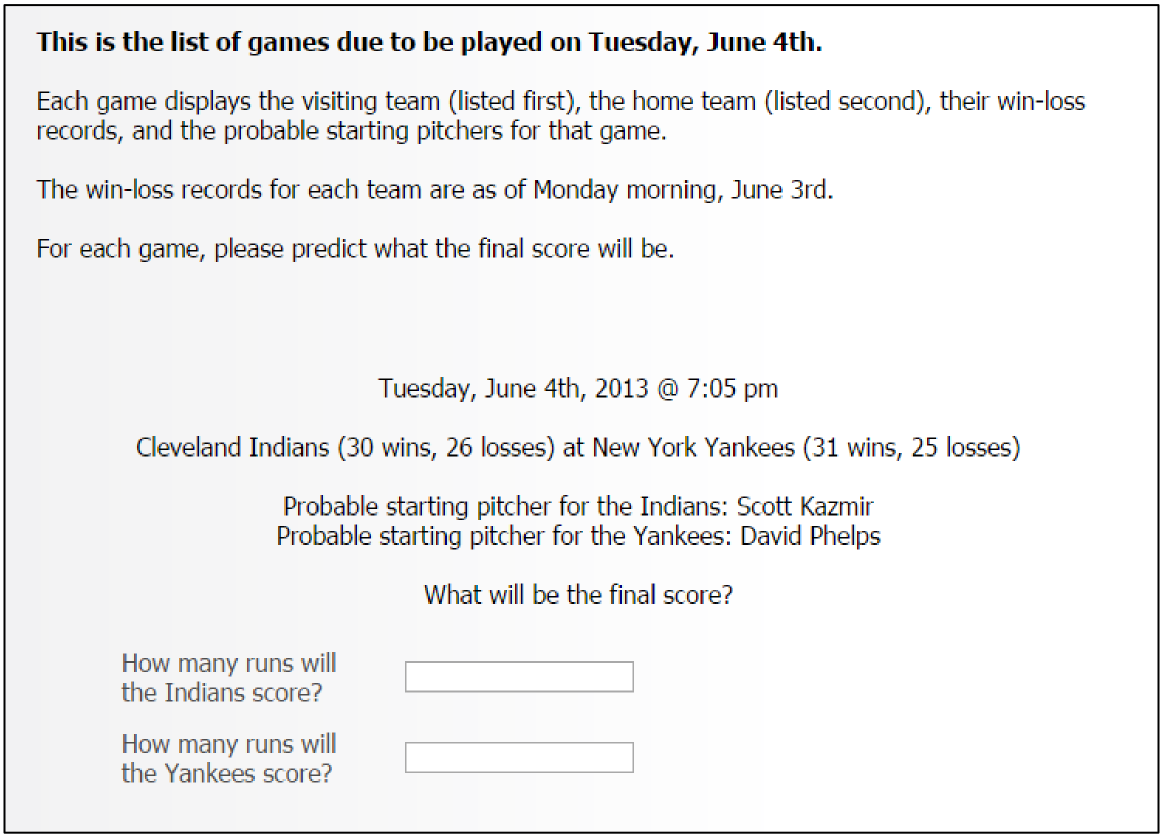
Cleveland Indians (30 wins, 26 losses) at New York Yankees (31 wins, 25 losses)

Probable starting pitcher for the Indians: Scott Kazmir
Probable starting pitcher for the Yankees: David Phelps

Which team will win the game?

Indians　　Yankees

Figure A1 15. Experiment 1: Score Only condition predictions.



This is the list of games due to be played on Tuesday, June 4th.

Each game displays the visiting team (listed first), the home team (listed second), their win-loss records, and the probable starting pitchers for that game.

The win-loss records for each team are as of Monday morning, June 3rd.

For each game, please predict what the final score will be.

Tuesday, June 4th, 2013 @ 7:05 pm

Cleveland Indians (30 wins, 26 losses) at New York Yankees (31 wins, 25 losses)

Probable starting pitcher for the Indians: Scott Kazmir
Probable starting pitcher for the Yankees: David Phelps

What will be the final score?

How many runs will the Indians score?

How many runs will the Yankees score?

Experiment 2

Table A1 2. Experiment 2 design.

Predictions	39 Major League Baseball games played on June 11th (15 games), June 12th (15 games), and June 13th (9 games) in 2013.
Run Date	June 10th, 2013
Conditions	Winner, Score Only, Score + Winner
Record information	Wins, losses, probable pitchers
Measures in the example that are NOT included in this experiment	· Prediction strategy · Motivation and confidence · Self-reported following and knowledge · Which sports they are interested in being contacted about.
Measures NOT in the example that ARE included in this experiment	· Maximizing Tendency Scale (included for an unrelated experiment).
Other deviations from the example format	· The Winner condition was incentivized 5 cents for correctly predicting the winner and the Score Only and Score + Winner conditions were incentivized 40 cents for correctly predicting the exact final score. · Participants were not reminded of the payoff amounts for each game. · The winner selection question was displayed before the score entry in the Score + Winner condition for each game.

Figure A1 16. Experiment 2: Winner condition predictions.

This is the list of games due to be played on Tuesday, June 11th.

Each game displays the visiting team (listed first), the home team (listed second), their win-loss records, and the probable starting pitchers for that game.

The win-loss records for each team are as of Monday morning, June 10th.

For each game, please predict who will win the game.

Tuesday, June 11th, 2013 @ 7:05 pm

Los Angeles Angels (27 wins, 36 losses) at Baltimore Orioles (35 wins, 28 losses)

Probable starting pitcher for the Angels: Jason Vargas
Probable starting pitcher for the Orioles: Miguel Gonzalez

Who will win the game?

Angels

Orioles

Figure A1 17. Experiment 2: Score Only condition predictions.

This is the list of games due to be played on Tuesday, June 11th.

Each game displays the visiting team (listed first), the home team (listed second), their win-loss records, and the probable starting pitchers for that game.

The win-loss records for each team are as of Monday morning, June 10th.

For each game, please predict what the final score will be.

Tuesday, June 11th, 2013 @ 7:05 pm

Los Angeles Angels (27 wins, 36 losses) at Baltimore Orioles (35 wins, 28 losses)

Probable starting pitcher for the Angels: Jason Vargas
Probable starting pitcher for the Orioles: Miguel Gonzalez

What will be the final score?

How many runs will the Angels score?

How many runs will the Orioles score?

Figure A1 18. Experiment 2: Score + Winner condition predictions.

This is the list of games due to be played on Tuesday, June 11th.

Each game displays the visiting team (listed first), the home team (listed second), their win-loss records, and the probable starting pitchers for that game.

The win-loss records for each team are as of Monday morning, June 10th.

For each game, please predict who will win the game and what the final score will be.

Tuesday, June 11th, 2013 @ 7:05 pm

Los Angeles Angels (27 wins, 36 losses) at Baltimore Orioles (35 wins, 28 losses)

Probable starting pitcher for the Angels: Jason Vargas
Probable starting pitcher for the Orioles: Miguel Gonzalez

Who will win the game?

Angels   Orioles

What will be the final score?

How many runs will the Angels score?

How many runs will the Orioles score?

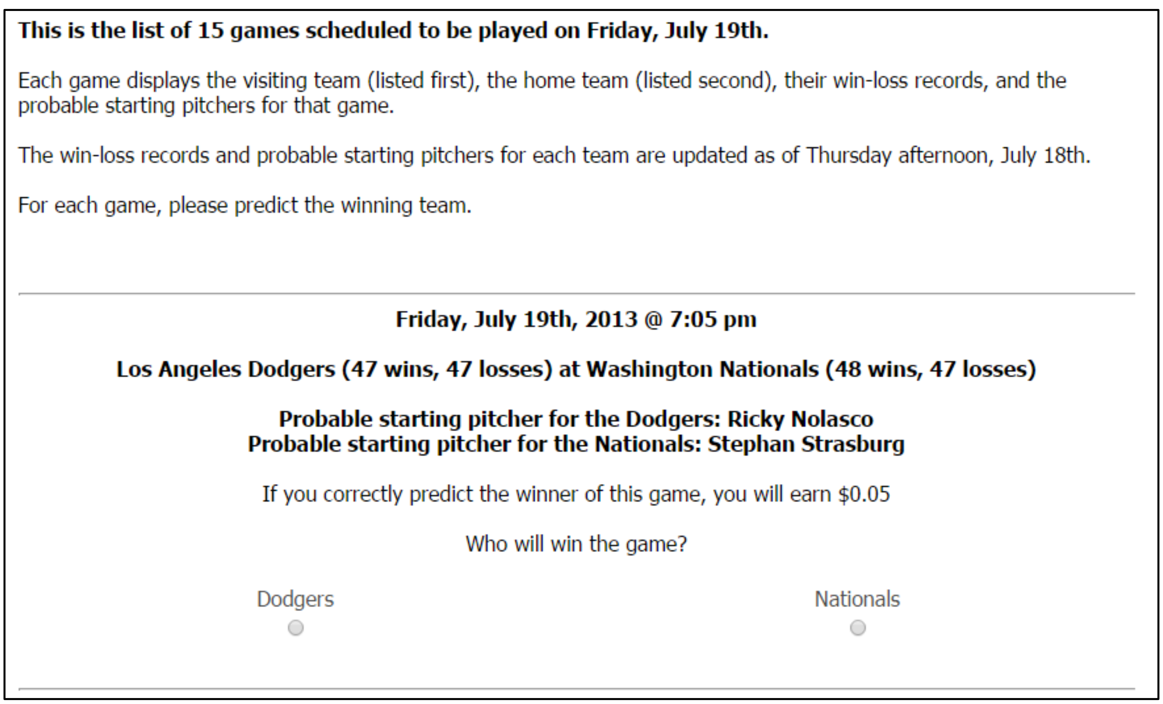
Note. Participants were incentivized for correctly predicting the exact final score.

Experiment 3

Table A1 3. Experiment 3 design.

Predictions	45 Major League Baseball games played on July 19th (15 games), July 20th (15 games), and July 21st (15 games) in 2013.
Run Date	July 18th, 2013.
Conditions	Winner, Score Only, Score + Winner (bonus for winner), Score + Winner (bonus for score)
Record information	Wins, losses, probable pitchers
Measures in the example that are NOT included in this experiment	· Self-reported following and knowledge · Which sports they are interested in being contacted about.
Other deviations from the example format	· The Winner condition and one of the Score + Winner conditions were incentivized $0.05 for correctly predicting the winner, while the Score Only condition and the other Score + Winner condition were incentivized $1.50 for correctly predicting the exact final score.

Figure A1 19. Experiment 3: Winner condition predictions.



This is the list of 15 games scheduled to be played on Friday, July 19th.

Each game displays the visiting team (listed first), the home team (listed second), their win-loss records, and the probable starting pitchers for that game.

The win-loss records and probable starting pitchers for each team are updated as of Thursday afternoon, July 18th.

For each game, please predict the winning team.

Friday, July 19th, 2013 @ 7:05 pm

Los Angeles Dodgers (47 wins, 47 losses) at Washington Nationals (48 wins, 47 losses)

Probable starting pitcher for the Dodgers: Ricky Nolasco
Probable starting pitcher for the Nationals: Stephan Strasburg

If you correctly predict the winner of this game, you will earn $0.05

Who will win the game?

Dodgers

Nationals

Figure A1 20. Experiment 3: Score Only condition predictions.

This is the list of 15 games scheduled to be played on Friday, July 19th.

Each game displays the visiting team (listed first), the home team (listed second), their win-loss records, and the probable starting pitchers for that game.

The win-loss records and probable starting pitchers for each team are updated as of Thursday afternoon, July 18th.

For each game, please predict the final score.

Friday, July 19th, 2013 @ 7:05 pm

Los Angeles Dodgers (47 wins, 47 losses) at Washington Nationals (48 wins, 47 losses)

Probable starting pitcher for the Dodgers: Ricky Nolasco
Probable starting pitcher for the Nationals: Stephan Strasburg

If you correctly predict the final score of this game, you will earn $1.50

How many runs will the **Dodgers** score?

How many runs will the **Nationals** score?

Figure A1 21. Experiment 3: Score + Winner condition predictions (incentivized for correct winning team selection).

This is the list of 15 games scheduled to be played on Friday, July 19th.

Each game displays the visiting team (listed first), the home team (listed second), their win-loss records, and the probable starting pitchers for that game.

The win-loss records and probable starting pitchers for each team are updated as of Thursday afternoon, July 18th.

For each game, please predict the final score and the winning team.

Friday, July 19th, 2013 @ 7:05 pm

Los Angeles Dodgers (47 wins, 47 losses) at Washington Nationals (48 wins, 47 losses)

Probable starting pitcher for the Dodgers: Ricky Nolasco
Probable starting pitcher for the Nationals: Stephan Strasburg

If you correctly predict the winner of this game, you will earn $0.05

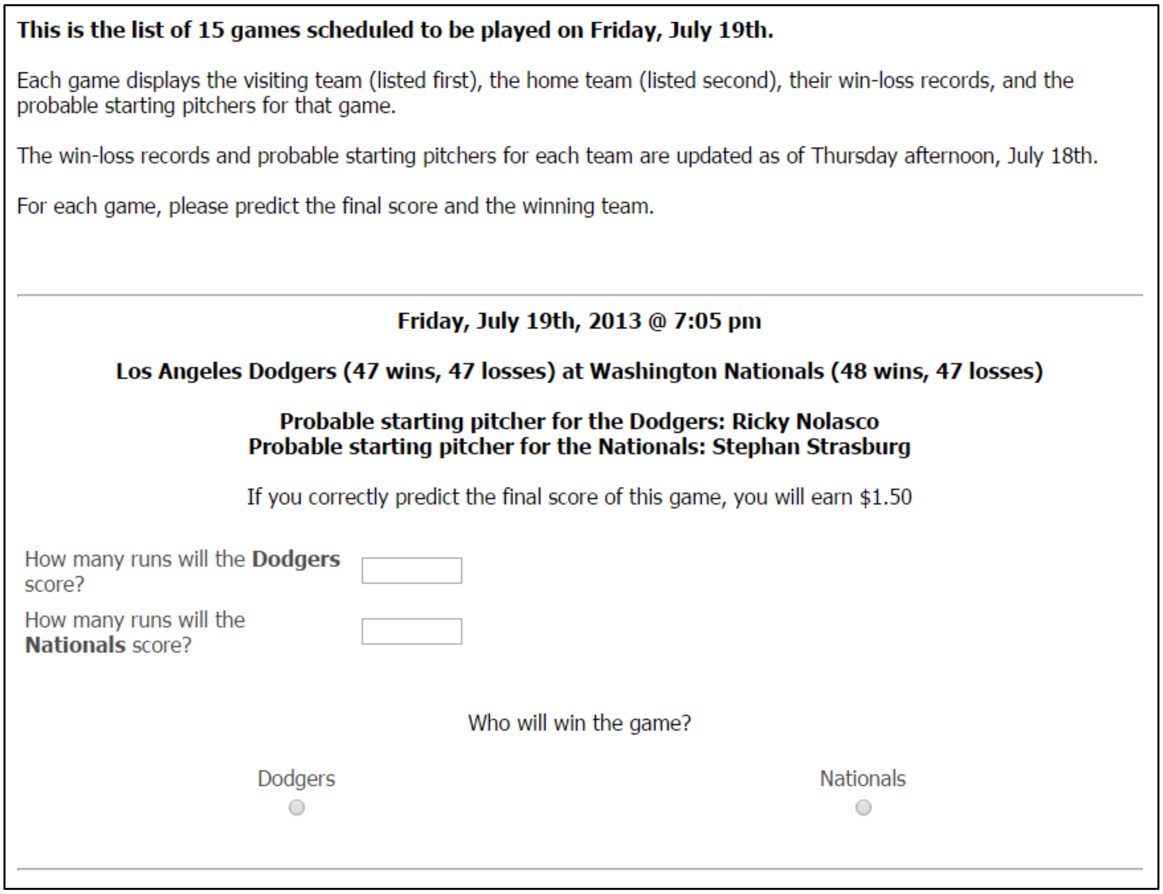
How many runs will the **Dodgers** score?

How many runs will the **Nationals** score?

Who will win the game?

Dodgers ○ Nationals ○

Figure A1 22. Experiment 3: Score + Winner condition predictions (incentivized for correct exact final score).


This is the list of 15 games scheduled to be played on Friday, July 19th.

Each game displays the visiting team (listed first), the home team (listed second), their win-loss records, and the probable starting pitchers for that game.

The win-loss records and probable starting pitchers for each team are updated as of Thursday afternoon, July 18th.

For each game, please predict the final score and the winning team.

Friday, July 19th, 2013 @ 7:05 pm

Los Angeles Dodgers (47 wins, 47 losses) at Washington Nationals (48 wins, 47 losses)

Probable starting pitcher for the Dodgers: Ricky Nolasco
Probable starting pitcher for the Nationals: Stephan Strasburg

If you correctly predict the final score of this game, you will earn $1.50

How many runs will the **Dodgers** score?

How many runs will the **Nationals** score?

Who will win the game?

Dodgers

Nationals

Experiment 4

Table A1 4. Experiment 4 design.

Predictions	45 Major League Baseball games played on July 26th (15 games), July 27th (15 games), and July 28th (15 games) in 2013.
Run Date	July 26th, 2013.
Conditions	Winner, Score + Winner, Hits + Winner, Runs + Winner
Record information	Wins, losses, probable pitchers
Measures in the example that are NOT included in this experiment	· Self-reported following and knowledge, · Which sports they are interested in being contacted about.

Figure A1 23. Experiment 4: Winner condition predictions.

This is the list of 15 games scheduled to be played on Friday, July 26th.

Each game displays the visiting team (listed first), the home team (listed second), their win-loss records, and the probable starting pitchers for that game.

The win-loss records and probable starting pitchers for each team are updated as of Thursday night, July 25th.

For each game, please predict the winning team.

Friday, July 26th, 2013 @ 7:05 pm

New York Mets (45 wins, 53 losses) at Washington Nationals (49 wins, 53 losses)

Probable starting pitcher for the Mets: Matt Harvey
Probable starting pitcher for the Nationals: Ross Ohlendorf

If you correctly predict the winner of this game, you will earn $0.05

Who will win the game?

Mets ○ Nationals ○

Figure A1 24. Experiment 4: Score + Winner condition predictions.

This is the list of 15 games scheduled to be played on Friday, July 26th.

Each game displays the visiting team (listed first), the home team (listed second), their win-loss records, and the probable starting pitchers for that game.

The win-loss records and probable starting pitchers for each team are updated as of Thursday night, July 25th.

For each game, please predict the final score and winning team.

Friday, July 26th, 2013 @ 7:05 pm

New York Mets (45 wins, 53 losses) at Washington Nationals (49 wins, 53 losses)

Probable starting pitcher for the Mets: Matt Harvey
Probable starting pitcher for the Nationals: Ross Ohlendorf

If you correctly predict the winner of this game, you will earn $0.05

How many runs will the **Mets** score?

How many runs will the **Nationals** score?

Who will win the game?

Mets

Nationals

Figure A1 25. Experiment 4: Hits + Winner condition instructions.

In this survey, you will predict the outcomes of the 45 Major League Baseball games scheduled to be played from Friday, July 26th through Sunday, July 28th.

Specifically, you will predict the **number of hits** each team will get and **winning team** for each game.

In baseball statistics, a hit is credited to a batter when the batter safely reaches first base after hitting the ball into fair territory, without the benefit of an error or a fielder's choice.

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Figure A1 26. Experiment 4: Hits + Winner condition predictions.

This is the list of 15 games scheduled to be played on Friday, July 26th.

Each game displays the visiting team (listed first), the home team (listed second), their win-loss records, and the probable starting pitchers for that game.

The win-loss records and probable starting pitchers for each team are updated as of Thursday night, July 25th.

For each game, please predict the number of hits each team will get and the winning team.

Friday, July 26th, 2013 @ 7:05 pm

New York Mets (45 wins, 53 losses) at Washington Nationals (49 wins, 53 losses)

Probable starting pitcher for the Mets: Matt Harvey
Probable starting pitcher for the Nationals: Ross Ohlendorf

If you correctly predict the winner of this game, you will earn $0.05

How many hits will the **Mets** get?

How many hits will the **Nationals** get?

Who will win the game?

Mets

Nationals

Figure A1 27. Experiment 4: Runs + Winner condition instructions.

In this survey, you will predict the outcomes of the 45 Major League Baseball games scheduled to be played from Friday, July 26th through Sunday, July 28th.

Specifically, you will predict the **total number of runs** and the **winning team** for each game.

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Figure A1 28. Experiment 4: Runs + Winner condition predictions.

This is the list of 15 games scheduled to be played on Friday, July 26th.

Each game displays the visiting team (listed first), the home team (listed second), their win-loss records, and the probable starting pitchers for that game.

The win-loss records and probable starting pitchers for each team are updated as of Thursday night, July 25th.

For each game, please predict the total number of runs and the winning team.

Friday, July 26th, 2013 @ 7:05 pm

New York Mets (45 wins, 53 losses) at Washington Nationals (49 wins, 53 losses)

Probable starting pitcher for the Mets: Matt Harvey
Probable starting pitcher for the Nationals: Ross Ohlendorf

If you correctly predict the winner of this game, you will earn $0.05

How many runs will be scored in this game?

Who will win the game?

Mets

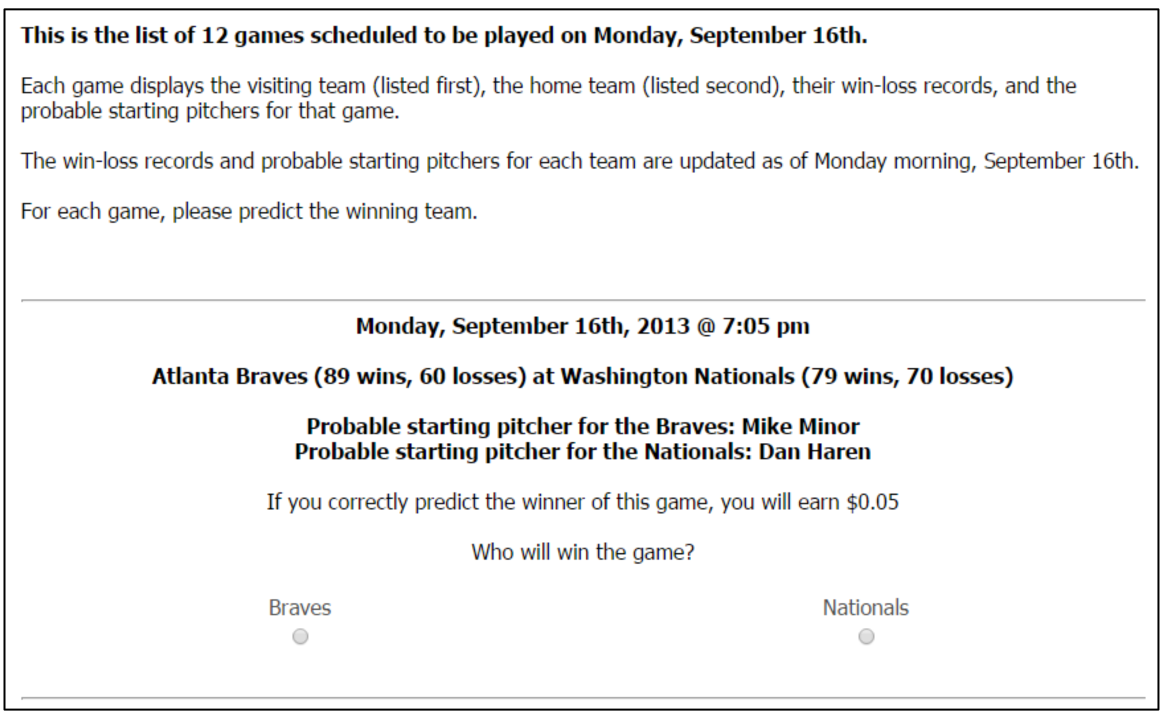
Nationals

Experiment 5

Table A1 5. Experiment 5 design.

Predictions	42 Major League Baseball games played on September 16^{th} (12 games), September 17^{th} (15 games), and September 18^{th} (15 games) in 2013.
Run Date	September 16^{th}, 2013
Conditions	Winner, Score + Winner, Runs + Winner, Time + Winner
Record information	Wins, losses, probable pitchers
Measures in the example that are NOT included in this experiment	· Self-reported following and knowledge · Which sports they are interested in being contacted about.

Figure A1 29. Experiment 5: Winner condition predictions.


This is the list of 12 games scheduled to be played on Monday, September 16th.

Each game displays the visiting team (listed first), the home team (listed second), their win-loss records, and the probable starting pitchers for that game.

The win-loss records and probable starting pitchers for each team are updated as of Monday morning, September 16th.

For each game, please predict the winning team.

Monday, September 16th, 2013 @ 7:05 pm

Atlanta Braves (89 wins, 60 losses) at Washington Nationals (79 wins, 70 losses)

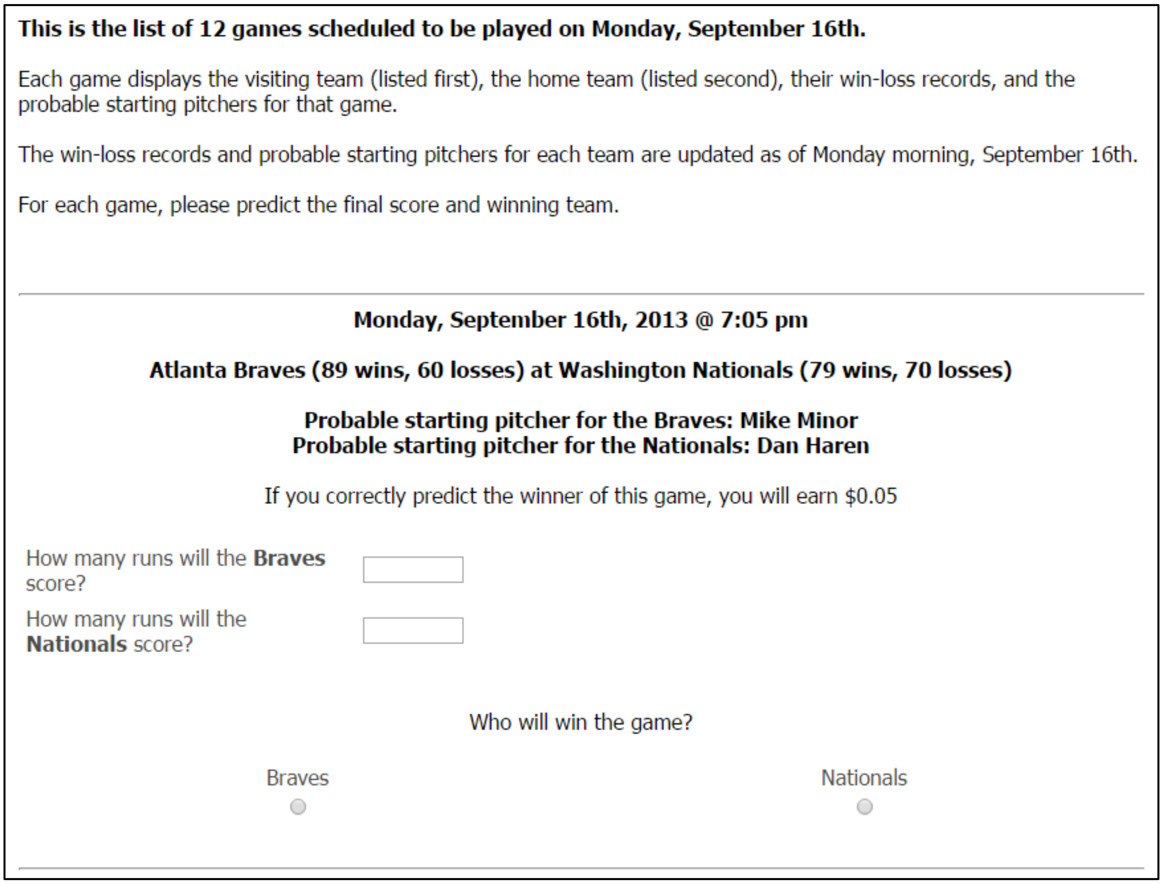
Probable starting pitcher for the Braves: Mike Minor
Probable starting pitcher for the Nationals: Dan Haren

If you correctly predict the winner of this game, you will earn $0.05

Who will win the game?

Braves Nationals

Figure A1 30. Experiment 5: Score + Winner condition predictions.



This is the list of 12 games scheduled to be played on Monday, September 16th.

Each game displays the visiting team (listed first), the home team (listed second), their win-loss records, and the probable starting pitchers for that game.

The win-loss records and probable starting pitchers for each team are updated as of Monday morning, September 16th.

For each game, please predict the final score and winning team.

Monday, September 16th, 2013 @ 7:05 pm

Atlanta Braves (89 wins, 60 losses) at Washington Nationals (79 wins, 70 losses)

Probable starting pitcher for the Braves: Mike Minor
Probable starting pitcher for the Nationals: Dan Haren

If you correctly predict the winner of this game, you will earn $0.05

How many runs will the **Braves** score?

How many runs will the **Nationals** score?

Who will win the game?

Braves

Nationals

Figure A1 31. Experiment 5: Runs + Winner condition predictions.

This is the list of 12 games scheduled to be played on Monday, September 16th.

Each game displays the visiting team (listed first), the home team (listed second), their win-loss records, and the probable starting pitchers for that game.

The win-loss records and probable starting pitchers for each team are updated as of Monday morning, September 16th.

For each game, please predict the total number of runs and winning team.

Monday, September 16th, 2013 @ 7:05 pm

Atlanta Braves (89 wins, 60 losses) at Washington Nationals (79 wins, 70 losses)

Probable starting pitcher for the Braves: Mike Minor
Probable starting pitcher for the Nationals: Dan Haren

If you correctly predict the winner of this game, you will earn $0.05

How many runs will be scored in this game?

Who will win the game?

Braves Nationals

Figure A1 32. Experiment 5: Time + Winner instructions.

In this survey, you will predict the outcomes of the 42 Major League Baseball games scheduled to be played from Monday, September 16th through Wednesday, September 19th.

Specifically, you will predict the **total game time** (in hours and minutes) and the **winning team** for each game.

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Figure A1 33. Time + Winner condition predictions.

This is the list of 12 games scheduled to be played on Monday, September 16th.

Each game displays the visiting team (listed first), the home team (listed second), their win-loss records, and the probable starting pitchers for that game.

The win-loss records and probable starting pitchers for each team are updated as of Monday morning, September 16th.

For each game, please predict the total game time and winning team.

Monday, September 16th, 2013 @ 7:05 pm

Atlanta Braves (89 wins, 60 losses) at Washington Nationals (79 wins, 70 losses)

Probable starting pitcher for the Braves: Mike Minor
Probable starting pitcher for the Nationals: Dan Haren

If you correctly predict the winner of this game, you will earn $0.05

How long will the game last?

Hours

Minutes

Who will win the game?

Braves

Nationals

Experiment 6

Table A1 6. Experiment 6 design.

Predictions	29 National Hockey League games played on January 16th (11 games), January 17th (2 games), January 18th (13 games), and January 19th (3 games) played in 2014.
Run Date	January 16th, 2014
Conditions	Predictions (Winner vs. Score + Winner) X Records (record info vs. no records)
Record information	Wins, losses, goals scored, goals allowed

Figure A1 34. Experiment 6: Winner condition predictions (with records).

This is the list of the 11 games scheduled to be played on Thursday January 16th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Goals Scored, and their Goals Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season, including Overtime Losses and Shootout Losses.
- **Goals Scored** is the total number of goals the team has scored against opponents in all previous games in the season.
- **Goals Allowed** is the total number of goals that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Thursday, January 16th.

For each game, please predict the **winning team**. You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Thursday, January 16th, 2014 @ 7:00 pm

Detroit Red Wings @ New York Rangers

Team	Wins	Losses	Goals Scored	Goals Allowed
Detroit Red Wings	20	26	118	127
New York Rangers	24	24	119	126

If you correctly predict the winner of this game, you will earn $0.05

Who will win the game?

Detroit Red Wings   New York Rangers

Figure A1 35. Experiment 6: Score + Winner condition predictions (with records).

This is the list of the 11 games scheduled to be played on Thursday January 16th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Goals Scored, and their Goals Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season, including Overtime Losses and Shootout Losses.
- **Goals Scored** is the total number of goals the team has scored against opponents in all previous games in the season.
- **Goals Allowed** is the total number of goals that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Thursday, January 16th.

For each game, please predict the **final score** and **winning team**. You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Thursday, January 16th, 2014 @ 7:00 pm

Detroit Red Wings @ New York Rangers

Team	Wins	Losses	Goals Scored	Goals Allowed
Detroit Red Wings	20	26	118	127
New York Rangers	24	24	119	126

If you correctly predict the winner of this game, you will earn $0.05

How many points will the **Detroit Red Wings** score?

How many points will the **New York Rangers** score?

Who will win the game?

Detroit Red Wings

New York Rangers

Figure A1 36. Experiment 6: Winner condition predictions (without records).

This is the list of the 11 games scheduled to be played on Thursday January 16th.

Each game displays the visiting team (listed first) and the home team (listed second).

All records are up to date as of Thursday, January 16th.

For each game, please predict the **winning team**. You will receive a $0.05 bonus from MTurk every time you correct predict the winner of a game.

Thursday, January 16th, 2014 @ 7:00 pm

Detroit Red Wings @ New York Rangers

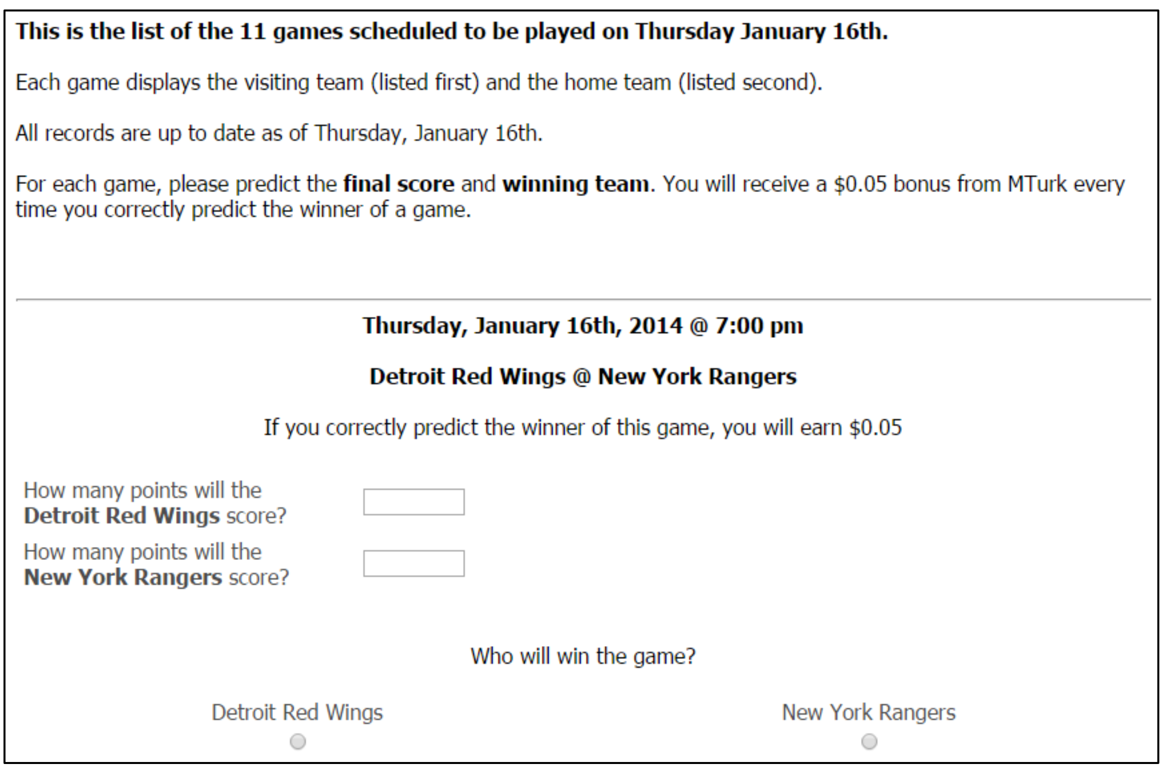
If you correctly predict the winner of this game, you will earn $0.05

Who will win the game?

Detroit Red Wings

New York Rangers

Figure A1 37. Experiment 6: Score + Winner condition predictions (without records).



This is the list of the 11 games scheduled to be played on Thursday January 16th.

Each game displays the visiting team (listed first) and the home team (listed second).

All records are up to date as of Thursday, January 16th.

For each game, please predict the **final score** and **winning team**. You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Thursday, January 16th, 2014 @ 7:00 pm

Detroit Red Wings @ New York Rangers

If you correctly predict the winner of this game, you will earn $0.05

How many points will the **Detroit Red Wings** score?

How many points will the **New York Rangers** score?

Who will win the game?

Detroit Red Wings

New York Rangers

Experiment 7

Table A1 7. Experiment 7 design.

Predictions	45 Major League Baseball games played on May 2^{nd} (15 games), May 3^{rd} (15 games), and May 4^{th} (15 games) in 2014.
Run Date	May 2^{nd}, 2014
Conditions	Winner vs. Score + Winner
Record information	Wins, losses, probable pitchers
Measures in the example that are NOT included in this experiment	· Prediction strategy
Measures NOT in the example that ARE included in this experiment	· Base rates · How difficult was the survey to understand
Other deviations from the example format	· After making their predictions, participants in all conditions revisited each game and said how many times the home team would win if they played that exact game 100 times.

Figure A1 38. Experiment 7: Winner condition predictions.

This is the list of the 15 Major League Baseball games scheduled to be played Friday May 2nd.

Each game displays the visiting team (listed first) and the home team (listed second). We also give you the Win/Loss records and probable pitchers for each team. All information is up to date as of 8:00am EST today, Friday May 2nd.

For each game, predict the **winning team.**

Each time you correctly predict the winning team, you will earn $0.05.

Friday May 2nd, 2014 at 2:20 pm

St. Louis Cardinals @ Chicago Cubs

Team	Wins	Losses	Probable Pitcher
St. Louis Cardinals	15	14	Adam Wainwright
Chicago Cubs	9	17	Travis Wood

If you correctly predict the winner of this game, you will earn $0.05

Who will win this game?

St. Louis Cardinals ○ Chicago Cubs ○

Figure A1 39. Experiment 7: Score + Winner condition predictions.

This is the list of the 15 Major League Baseball games scheduled to be played Friday May 2nd.

Each game displays the visiting team (listed first) and the home team (listed second). We also give you the Win/Loss records and probable pitchers for each team. All information is up to date as of 8:00am EST today, Friday May 2nd.

For each game, please predict the **final score**, predict the **winning team.**

Each time you correctly predict the winning team, you will earn $0.05.

Friday May 2nd, 2014 at 2:20 pm

St. Louis Cardinals @ Chicago Cubs

Team	Wins	Losses	Probable Pitcher
St. Louis Cardinals	15	14	Adam Wainwright
Chicago Cubs	9	17	Travis Wood

If you correctly predict the winner of this game, you will earn $0.05

What will the final score of this game be?

How many runs will the **St. Louis Cardinals** score?

How many runs will the **Chicago Cubs** score?

Who will win this game?

St. Louis Cardinals

Chicago Cubs

Figure A1 40. Experiment 7: Base rates instructions (all conditions).

In this section, you will once again show you the **45 Major League Baseball games** scheduled to be played from Friday May 2nd through Sunday May 4th.

For each game, we will ask you to **imagine that the two teams played that exact game 100 times**.

What we mean by "that exact game" is that each of the 100 times the game is played, the game would begin with the exact same starting conditions as the actual game.

For example, the location and home team, the win/loss records of each team, the pitchers, the player lineup, player injuries, etc. would all be the same at the beginning of each of the 100 games as they are at the beginning of the actual game.

For each game, we will ask you to tell us **how many times you think the home team would win** if that exact game were played 100 times.

Figure A1 41. Experiment 7: Base rates (all conditions).

This is the list of the 15 Major League Baseball games scheduled to be played Friday May 2nd.

Each game displays the visiting team (listed first) and the home team (listed second). We also give you the Win/Loss records and probable pitchers for each team. All information is up to date as of 8:00am EST today, Friday May 2nd.

For each game, we will ask you to **imagine that the two teams played that exact game 100 times**.

What we mean by "that exact game" is that each of the 100 times the game is played, the game would begin with the exact same starting conditions as the actual game.

For example, the location and home team, the win/loss records of each team, the pitchers, the player lineup, player injuries, etc. would all be the same at the beginning of each of the 100 games as they are at the beginning of the actual game.

For each game, we will ask you to tell us **how many times you think the home team would win** if that exact game were played 100 times.

Friday May 2nd, 2014 at 2:20 pm

St. Louis Cardinals @ Chicago Cubs

Team	Wins	Losses	Probable Pitcher
St. Louis Cardinals	15	14	Adam Wainwright
Chicago Cubs	9	17	Travis Wood

Imagine these two teams played this exact game 100 times.

How many games (out of 100) do you think the **Chicago Cubs** would win?

Experiment 8

This experiment is a replication of Experiment 4 with changes in the display format and two additional sets of measures after the predictions.

Table A1 8. Experiment 8 design.

Predictions	44 Major League Baseball games played on May 5th (13 games), May 6th (15 games), and May 7th (16 games) in 2014.
Run Date	May 5th, 2014
Conditions	Winner, Score + Winner, Hits + Winner, Runs + Winner
Record information	Wins, losses, probable pitchers
Measures NOT in the example that ARE included in this experiment	· Outcome variability · Outcome usefulness for predicting the winner

Figure A1 42. Experiment 8: Winner condition predictions.

This is the list of the 13 Major League Baseball games scheduled to be played Monday May 5th.

Each game displays the visiting team (listed first) and the home team (listed second). We also give you the Win/Loss records and probable pitchers for each team. All information is up to date as of 8:00am EST today, Monday May 5th.

For each game, please predict the **winning team.**

Each time you correctly predict the winning team, you will earn $0.05.

Monday May 5th, 2014 at 7:05 pm

Minnesota Twins @ Cleveland Indians

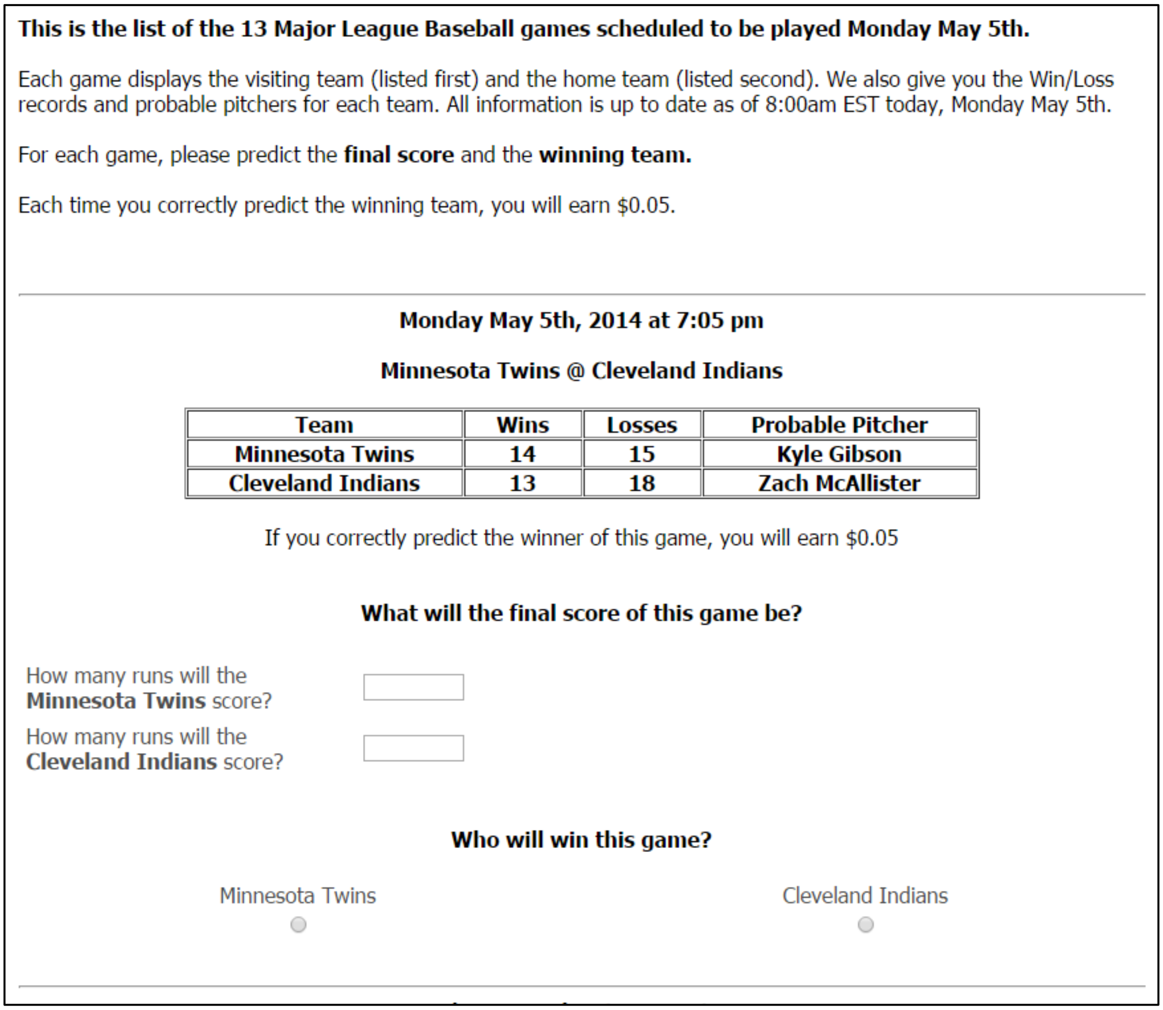
Team	Wins	Losses	Probable Pitcher
Minnesota Twins	14	15	Kyle Gibson
Cleveland Indians	13	18	Zach McAllister

If you correctly predict the winner of this game, you will earn $0.05

Who will win this game?

Minnesota Twins ○ Cleveland Indians ○

Figure A1 43. Experiment 8: Score + Winner condition predictions.



This is the list of the 13 Major League Baseball games scheduled to be played Monday May 5th.

Each game displays the visiting team (listed first) and the home team (listed second). We also give you the Win/Loss records and probable pitchers for each team. All information is up to date as of 8:00am EST today, Monday May 5th.

For each game, please predict the **final score** and the **winning team.**

Each time you correctly predict the winning team, you will earn $0.05.

Monday May 5th, 2014 at 7:05 pm

Minnesota Twins @ Cleveland Indians

Team	Wins	Losses	Probable Pitcher
Minnesota Twins	14	15	Kyle Gibson
Cleveland Indians	13	18	Zach McAllister

If you correctly predict the winner of this game, you will earn $0.05

What will the final score of this game be?

How many runs will the **Minnesota Twins** score?

How many runs will the **Cleveland Indians** score?

Who will win this game?

Minnesota Twins

Cleveland Indians

Figure A1 44. Experiment 8: Hits + Winner condition predictions.

This is the list of the 13 Major League Baseball games scheduled to be played Monday May 5th.

Each game displays the visiting team (listed first) and the home team (listed second). We also give you the Win/Loss records and probable pitchers for each team. All information is up to date as of 8:00am EST today, Monday May 5th.

For each game, please predict the **number of hits** each team will get and the **winning team.**

In baseball statistics, a hit is credited to a batter when the batter safely reaches first base after hitting the ball into fair territory, without the benefit of an error or a fielder's choice.

Each time you correctly predict the winning team, you will earn $0.05.

Monday May 5th, 2014 at 7:05 pm

Minnesota Twins @ Cleveland Indians

Team	Wins	Losses	Probable Pitcher
Minnesota Twins	14	15	Kyle Gibson
Cleveland Indians	13	18	Zach McAllister

If you correctly predict the winner of this game, you will earn $0.05

How many hits will each team get?

How many hits will the **Minnesota Twins** get?

How many hits will the **Cleveland Indians** get?

Who will win this game?

Minnesota Twins

Cleveland Indians

Figure A1 45. Experiment 8: Runs + Winner condition predictions.

This is the list of the 13 Major League Baseball games scheduled to be played Monday May 5th.

Each game displays the visiting team (listed first) and the home team (listed second). We also give you the Win/Loss records and probable pitchers for each team. All information is up to date as of 8:00am EST today, Monday May 5th.

For each game, please predict the **total number of runs** and the **winning team.**

Each time you correctly predict the winning team, you will earn $0.05.

Monday May 5th, 2014 at 7:05 pm

Minnesota Twins @ Cleveland Indians

Team	Wins	Losses	Probable Pitcher
Minnesota Twins	14	15	Kyle Gibson
Cleveland Indians	13	18	Zach McAllister

If you correctly predict the winner of this game, you will earn $0.05

What will be the total number of runs scored by both teams?

How many runs will be scored during this game?

Who will win this game?

Minnesota Twins

Cleveland Indians

Experiment 9

The format of this experiment is an exact replication of Experiment 7, with the exception that the question about how difficult the survey was to understand was changed to "how confusing were the instructions".

Table A1 9. Experiment 9 design.

Predictions	41 Major League Baseball games played on June 3rd (15 games), June 4th (15 games), and June 5th (11 games) in 2014.
Run Date	June 3rd, 2014
Conditions	Winner vs. Score + Winner
Record information	Wins, losses, probable pitchers
Measures in the example that are NOT included in this experiment	· Prediction strategy
Measures NOT in the example that ARE included in this experiment	· Base rates · How confusing were the instructions in the survey
Other deviations from the example format	· After making their predictions, participants in all conditions revisited each game and said how many times the home team would win if they played that exact game 100 times.

Experiment 10

The format of this experiment is an exact replication of Experiment 8.

Table A1 10. Experiment 10 design.

Predictions	44 Major League Baseball games played on June 6th (14 games), June 7th (15 games), and June 8th (15 games) in 2014.
Run Date	June 6th, 2014.
Conditions	Winner, Score + Winner, Hits + Winner, Runs + Winner
Record information	Wins, losses, probable pitchers
Measures NOT in the example that ARE included in this experiment	· outcome variability · outcome usefulness for predicting the winner

Experiment 11

The format of this experiment is an exact replication of Experiments 7 and 9.

Table A1 11. Experiment 11 design.

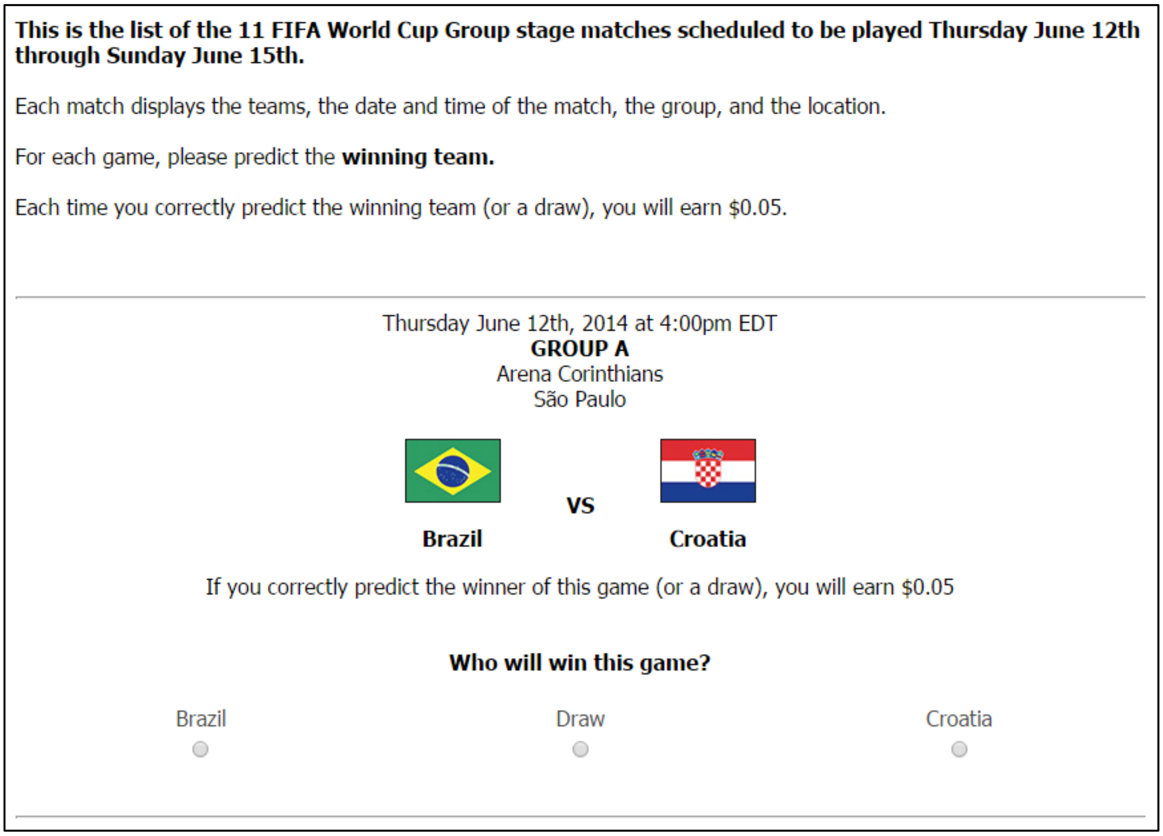
Predictions	42 Major League Baseball games played on June 9th (12 games), June 10th (15 games), and June 11th (15 games) in 2014.
Run Date	June 9th, 2014
Conditions	Winner vs. Score + Winner
Record information	Wins, losses, probable pitchers
Measures in the example that are NOT included in this experiment	· Prediction strategy
Measures NOT in the example that ARE included in this experiment	· Base rates · How confusing were the instructions in the survey
Other deviations from the example format	· After making their predictions, participants in all conditions revisited each game and said how many times the home team would win if they played that exact game 100 times.

Experiment 12

Table A1 12. Experiment 12 design.

Predictions	48 Fédération Internationale de Football Association (FIFA) 2014 World Cup Group Stage matches played on June 12th to June 15th (11 games), June 16th to June 19th (12 games), June 20th to June 23rd (13 games), and June 24th to June 26th (12 games).
Run Date	June 11th, 2014
Conditions	Winner, Score + Winner
Record information	Wins, losses, probable pitchers
Measures NOT in the example that ARE included in this experiment	· Team liking ratings
Other deviations from the example format	· Each page spans multiple days; 4 pages of predictions total. · There are no "home" and "visiting" team designations. · No team records were given. · Participants were permitted to enter tied scores and to choose "Draw" for the game outcome.

Figure A1 46. Experiment 12: Winner condition predictions.



This is the list of the 11 FIFA World Cup Group stage matches scheduled to be played Thursday June 12th through Sunday June 15th.

Each match displays the teams, the date and time of the match, the group, and the location.

For each game, please predict the **winning team.**

Each time you correctly predict the winning team (or a draw), you will earn $0.05.

Thursday June 12th, 2014 at 4:00pm EDT
GROUP A
Arena Corinthians
São Paulo

Brazil **VS** **Croatia**

If you correctly predict the winner of this game (or a draw), you will earn $0.05

Who will win this game?

Brazil Draw Croatia

Figure A1 47. Experiment 12: Score + Winner condition predictions.

This is the list of the 11 FIFA World Cup Group stage matches scheduled to be played Thursday June 12th through Sunday June 15th.

Each match displays the teams, the date and time of the match, the group, and the location.

For each game, please predict the **final score** and the **winning team.**

Each time you correctly predict the winning team (or a draw), you will earn $0.05.

Thursday June 12th, 2014 at 4:00pm EDT
GROUP A
Arena Corinthians
São Paulo

VS

Brazil **Croatia**

If you correctly predict the winner of this game (or a draw), you will earn $0.05

What will the final score of this game be?

How many goals will **Brazil** score?

How many goals will **Croatia** score?

Who will win this game?

Brazil Draw Croatia

Experiment 13

Table A1 13. Experiment 13 design.

Predictions	32 National Basketball Association games played on November 12th (8 games), November 13th (4 games), November 14th (10 games), and November 15th (10 games).
Run Date	November 12th, 2014
Conditions	Winner, Score + Winner
Record information	Wins, losses
Measures in the example that are NOT included in this experiment	• Prediction strategy
Measures NOT in the example that ARE included in this experiment	• How carefully they thought about their predictions • How much effort they invested in making their predictions
Other deviations from the example format	· Participants first made 16 predictions about games that were worth 5 cents for correct winning team predictions, then answered self-report measures for those 16 games, then made an additional 16 predictions about games that were worth 25 cents for correct winning team predictions, then answered self-report measures for those 16 games. · Before each set of 16 predictions, participants had to pass a comprehension check indicating how much they would get paid for each correct prediction. · Which games were worth the 5 cent bonus and 25 cent bonus was randomized between subjects. Half of the games on each day were assigned to be either 5-cent or 25-cent games, and so each page only displayed half of the days' games since 5-cent games and 25-cent games were predicted separately.

Figure A1 48. Experiment 13: Winner condition instructions (small bonus).

In this portion of the survey, you will predict the outcomes of **16 National Basketball Association games** scheduled to be played on Wednesday, November 12th through Saturday, November 15th.

Specifically, you will predict the **winning team** for each game.

You will receive a **$0.05 bonus** from MTurk every time you correctly predict the winner of a game.

To show that you understand the task, please enter the dollar amount of the bonus you will receive each time you correctly predict the winner of a game:

Figure A1 49. Experiment 13: Winner condition predictions (small bonus).

This is a list of 4 of the games scheduled to be played on Wednesday, November 12th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given the number of games they have won and lost so far this season. All records are up to date as of Wednesday, November 12th at 8:00am ET.

For each game, please predict the **winning team.**

You will receive a **$0.05 bonus** from MTurk every time you correctly predict the winner of a game.

Wednesday, November 12th, 2014 at 7:30 pm

Utah Jazz (3 wins, 5 losses) @ **Atlanta Hawks** (3 wins, 3 losses)

If you correctly predict the winner of this game, you will earn **$0.05**

Who will win this game?

Utah Jazz Atlanta Hawks

Figure A1 50. Experiment 13: Winner condition instructions (large bonus).

In this portion of the survey, you will predict the outcomes of **16 different National Basketball Association games** scheduled to be played on Wednesday, November 12th through Saturday, November 15th. <u>These 16 games are different games than the ones you made predictions about earlier</u>.

Specifically, you will predict the **winning team** for each game.

You will receive a **$0.25 bonus** from MTurk every time you correctly predict the winner of a game.

To show that you understand the task, please enter the dollar amount of the bonus you will receive each time you correctly predict the winner of a game:

Figure A1 51. Experiment 13: Winner condition predictions (large bonus).

This is a list of 4 of the games scheduled to be played on Wednesday, November 12th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given the number of games they have won and lost so far this season. All records are up to date as of Wednesday, November 12th at 8:00am ET.

For each game, please predict the **winning team.**

You will receive a **$0.25 bonus** from MTurk every time you correctly predict the winner of a game.

Wednesday, November 12th, 2014 at 7:30 pm

Utah Jazz (3 wins, 5 losses) @ **Atlanta Hawks** (3 wins, 3 losses)

If you correctly predict the winner of this game, you will earn **$0.25**

Who will win this game?

Utah Jazz ○ Atlanta Hawks ○

Figure A1 52. Experiment 13: Score + Winner condition instructions (small bonus).

In this portion of the survey, you will predict the outcomes of **16 National Basketball Association games** scheduled to be played on Wednesday, November 12th through Saturday, November 15th.

Specifically, you will predict the **final score** and **winning team** for each game.

You will receive a **$0.05 bonus** from MTurk every time you correctly predict the winner of a game.

To show that you understand the task, please enter the amount of the bonus you will receive each time you correctly predict the winner of a game:

Figure A1 53. Experiment 13: Score + Winner condition predictions (small bonus).

This is a list of 4 of the games scheduled to be played on Wednesday, November 12th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given the number of games they have won and lost so far this season. All records are up to date as of Wednesday, November 12th at 8:00am ET.

For each game, please predict the **final score** and the **winning team.**

You will receive a **$0.05 bonus** from MTurk every time you correctly predict the winner of a game.

Wednesday, November 12th, 2014 at 7:30 pm

Utah Jazz (3 wins, 5 losses) @ **Atlanta Hawks** (3 wins, 3 losses)

If you correctly predict the winner of this game, you will earn **$0.05**

What will the final score of this game be?

How many points will the **Utah Jazz** score?

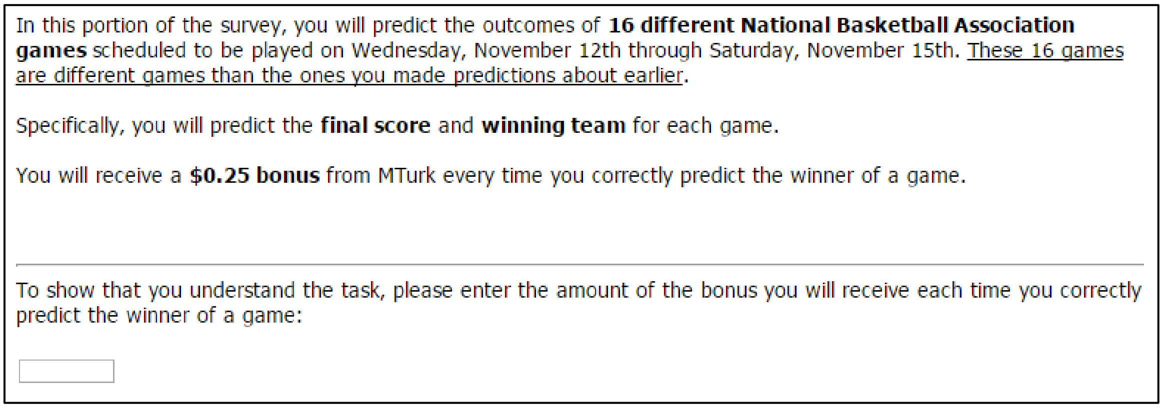
How many points will the **Atlanta Hawks** score?

Who will win this game?

Utah Jazz

Atlanta Hawks

Figure A1 54. Experiment 13: Score + Winner condition instructions (large bonus).



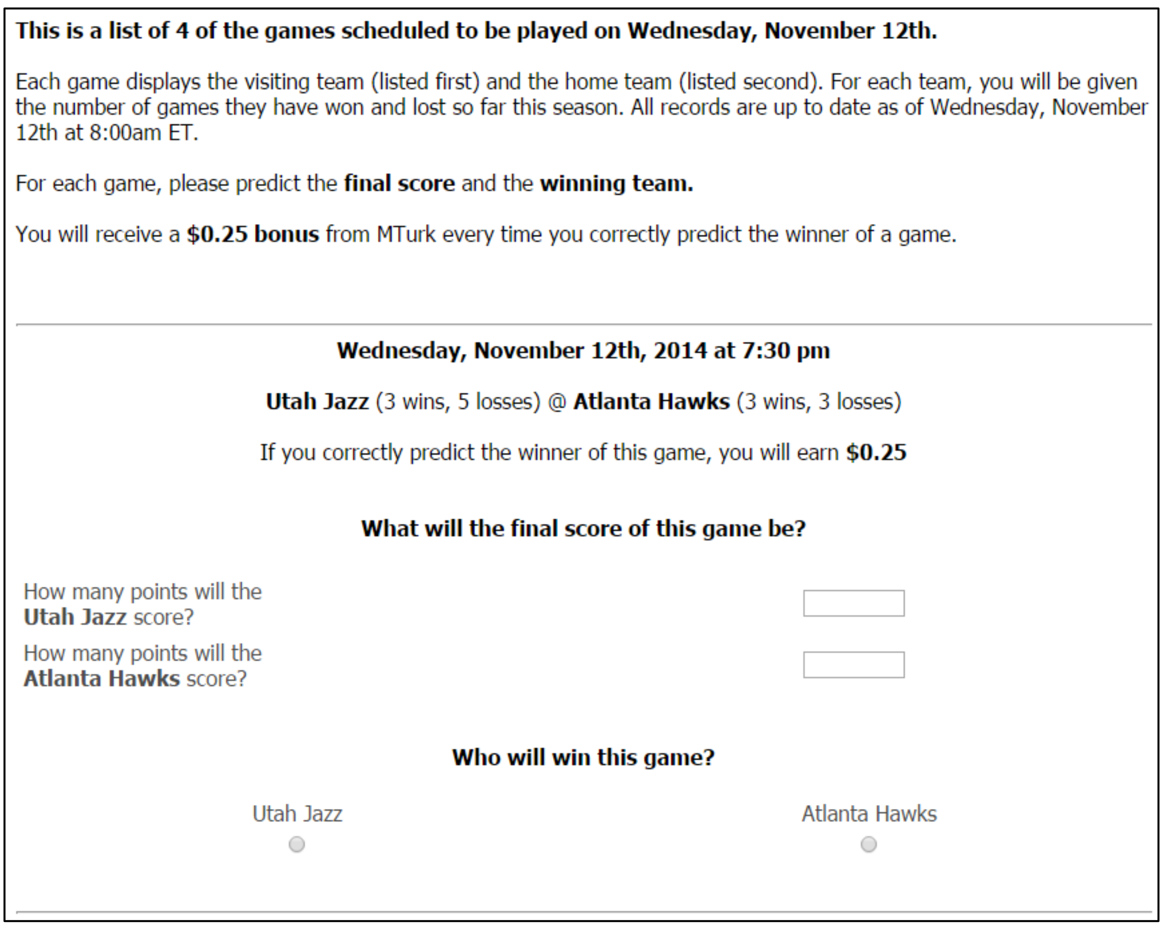
In this portion of the survey, you will predict the outcomes of **16 different National Basketball Association games** scheduled to be played on Wednesday, November 12th through Saturday, November 15th. <u>These 16 games are different games than the ones you made predictions about earlier</u>.

Specifically, you will predict the **final score** and **winning team** for each game.

You will receive a **$0.25 bonus** from MTurk every time you correctly predict the winner of a game.

To show that you understand the task, please enter the amount of the bonus you will receive each time you correctly predict the winner of a game:

Figure A1 55. Experiment 13: Score + Winner condition predictions (large bonus).



This is a list of 4 of the games scheduled to be played on Wednesday, November 12th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given the number of games they have won and lost so far this season. All records are up to date as of Wednesday, November 12th at 8:00am ET.

For each game, please predict the **final score** and the **winning team.**

You will receive a **$0.25 bonus** from MTurk every time you correctly predict the winner of a game.

Wednesday, November 12th, 2014 at 7:30 pm

Utah Jazz (3 wins, 5 losses) @ **Atlanta Hawks** (3 wins, 3 losses)

If you correctly predict the winner of this game, you will earn **$0.25**

What will the final score of this game be?

How many points will the **Utah Jazz** score?

How many points will the **Atlanta Hawks** score?

Who will win this game?

Utah Jazz

Atlanta Hawks

Experiment 14

Experiment 14 was a replication of Experiment 13 in the domain of hockey. The only difference in the design is that we added the base rates task to the end of the survey.

Table A1 14. Experiment 14 design.

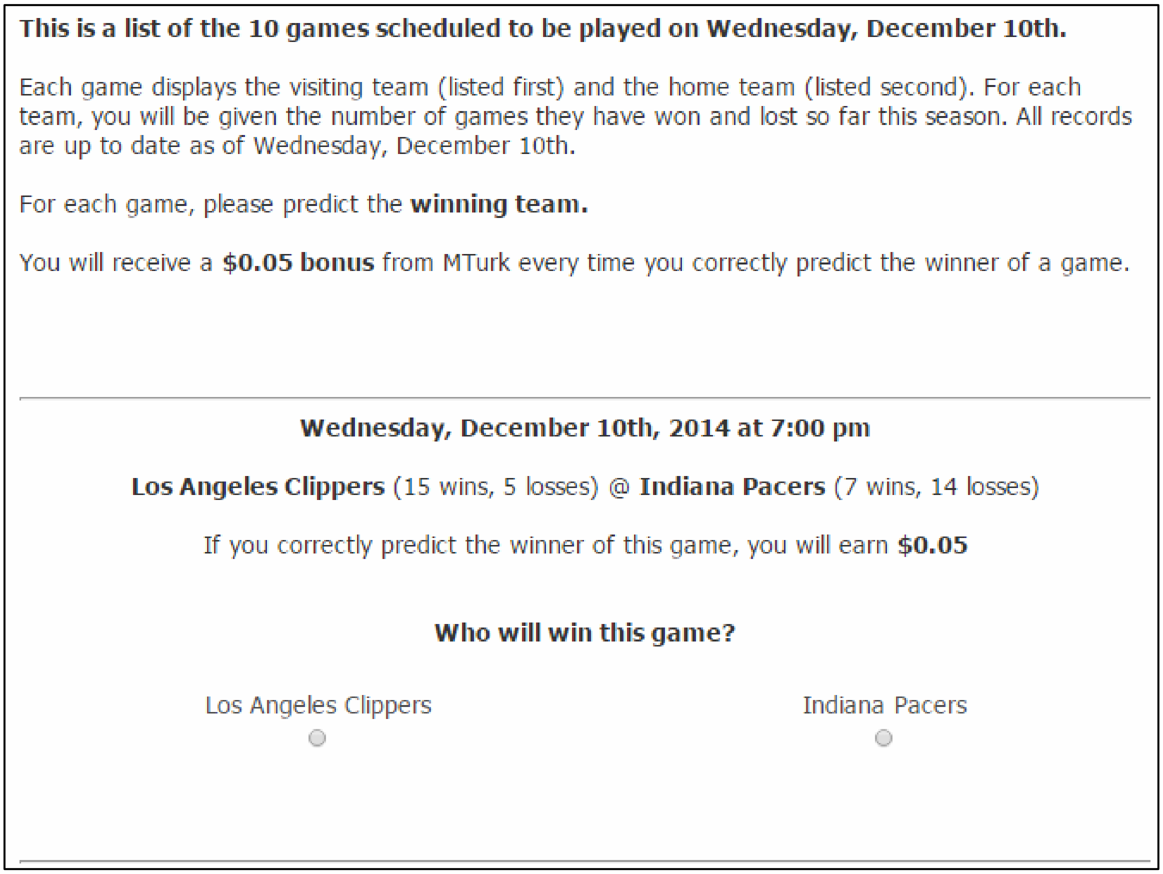
Predictions	32 National Hockey League games played on November 20th (12 games), November 21st (4 games), November 22nd (12 games), and November 23rd (4 games).
Run Date	November 20th, 2014
Conditions	Winner, Score + Winner
Record information	Wins, losses (with regulation losses and overtime losses displayed separately)
Measures in the example that are NOT included in this experiment	· Prediction strategy
Measures NOT in the example that ARE included in this experiment	· Base rates · How carefully they thought about their predictions · How much effort they invested in making their predictions · How confusing were the instructions in the survey
Other deviations from the example format	· Participants first made 16 predictions about games that were worth 5 cents for correct winning team predictions, then answered self-report measures for those 16 games, then made an additional 16 predictions about games that were worth 25 cents for correct winning team predictions, then answered self-report measures for those 16 games. · Before each set of 16 predictions, participants had to pass a comprehension check indicating how much they would get paid for each correct prediction. · Which games were worth the 5 cent bonus and 25 cent bonus was randomized between subjects. Half of the games on each day were assigned to be either 5-cent or 25-cent games, and so each page only displayed half of the days' games since 5-cent games and 25-cent games were predicted separately. · Participants in all conditions revisited each game and said how many times the home team would win if they were to play that exact game 100 times.

Experiment 15

Table A1 15. Experiment 15 design.

Predictions	32 National Basketball Association games played on December 10th (10 games), December 11th (2 games), December 12th (12 games), and December 13th (8 games).
Run Date	December 10th, 2014
Conditions	Winner, Score + Winner, Free Throws + Winner, Temperature + Winner
Record information	Wins, losses
Measures in the example that are NOT included in this experiment	· Prediction strategy
Measures NOT in the example that ARE included in this experiment	· Base rates · How confusing were the instructions in the survey
Other deviations from the example format	· Participants were paid 60 cents for completing the study. · After making their predictions, participants in all conditions revisited each game and said how many times each team would win if they were to play that exact game 100 times.

Figure A1 56. Experiment 15: Winner condition predictions.



This is a list of the 10 games scheduled to be played on Wednesday, December 10th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given the number of games they have won and lost so far this season. All records are up to date as of Wednesday, December 10th.

For each game, please predict the **winning team.**

You will receive a **$0.05 bonus** from MTurk every time you correctly predict the winner of a game.

Wednesday, December 10th, 2014 at 7:00 pm

Los Angeles Clippers (15 wins, 5 losses) @ **Indiana Pacers** (7 wins, 14 losses)

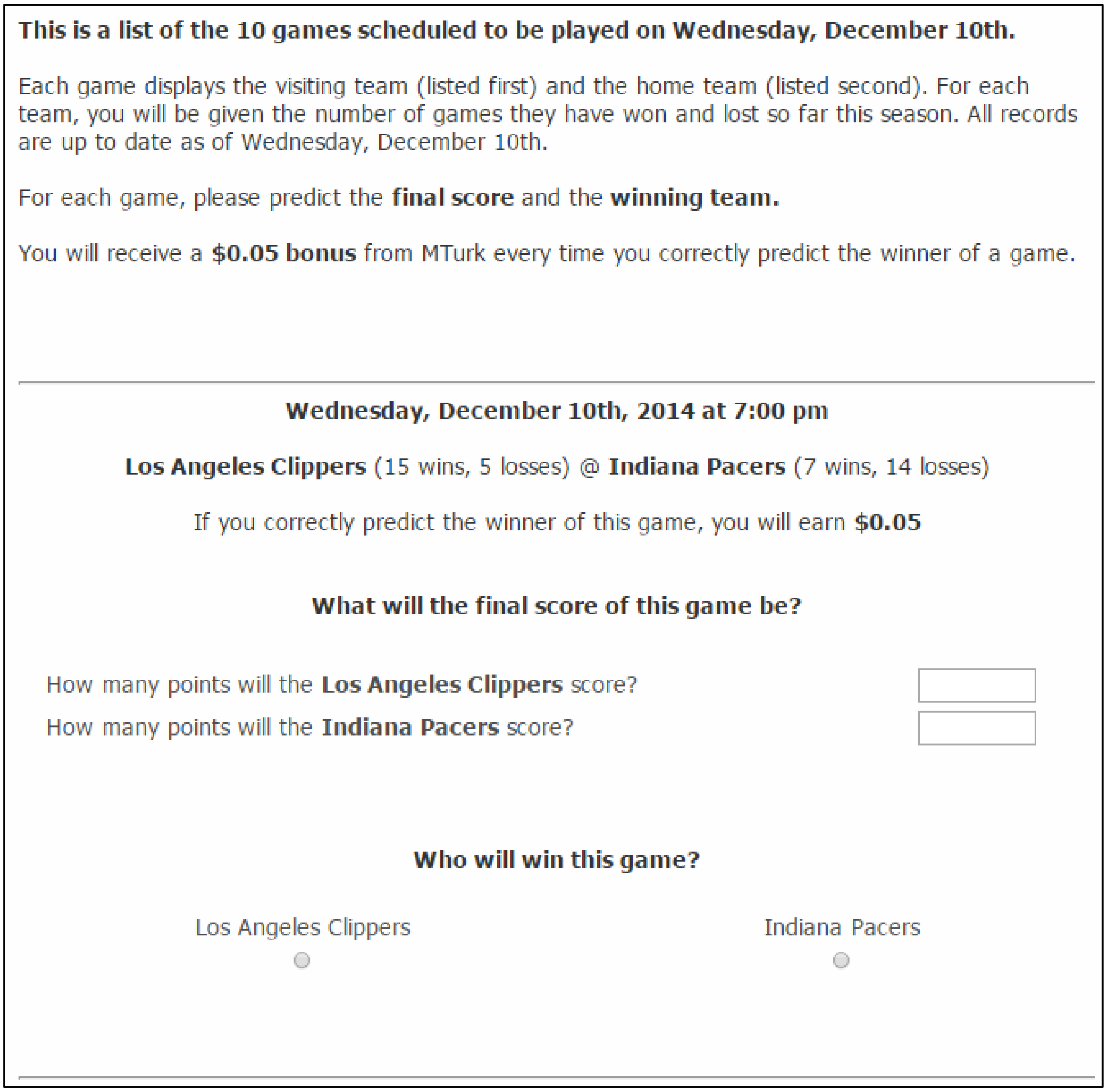
If you correctly predict the winner of this game, you will earn **$0.05**

Who will win this game?

Los Angeles Clippers

Indiana Pacers

Figure A1 57. Experiment 15: Score + Winner condition predictions.



This is a list of the 10 games scheduled to be played on Wednesday, December 10th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given the number of games they have won and lost so far this season. All records are up to date as of Wednesday, December 10th.

For each game, please predict the **final score** and the **winning team.**

You will receive a **$0.05 bonus** from MTurk every time you correctly predict the winner of a game.

Wednesday, December 10th, 2014 at 7:00 pm

Los Angeles Clippers (15 wins, 5 losses) @ **Indiana Pacers** (7 wins, 14 losses)

If you correctly predict the winner of this game, you will earn **$0.05**

What will the final score of this game be?

How many points will the **Los Angeles Clippers** score?

How many points will the **Indiana Pacers** score?

Who will win this game?

Los Angeles Clippers

Indiana Pacers

Figure A1 58. Experiment 15: Free Throws + Winner condition instructions.

In this portion of the survey, you will predict the outcomes of **32 National Basketball Association games** scheduled to be played on Wednesday, December 10th through Saturday, December 13th.

Specifically, you will predict the **how many free throws each team will attempt** and the **winning team** for each game.

You will receive a **$0.05 bonus** from MTurk every time you correctly predict the winner of a game.

Figure A1 59. Experiment 15: Free Throws + Winner condition predictions.

This is a list of the 10 games scheduled to be played on Wednesday, December 10th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given the number of games they have won and lost so far this season. All records are up to date as of Wednesday, December 10th.

For each game, please predict the **how many free throws each team will attempt** and the **winning team.**

You will receive a **$0.05 bonus** from MTurk every time you correctly predict the winner of a game.

Wednesday, December 10th, 2014 at 7:00 pm

Los Angeles Clippers (15 wins, 5 losses) @ **Indiana Pacers** (7 wins, 14 losses)

If you correctly predict the winner of this game, you will earn **$0.05**

How many free throws will each team attempt?

How many free throws will the **Los Angeles Clippers** attempt?

How many free throws will the **Indiana Pacers** attempt?

Who will win this game?

Los Angeles Clippers

Indiana Pacers

Figure A1 60. Experiment 15: Temperature + Winner condition instructions.

In this portion of the survey, you will predict the outcomes of **32 National Basketball Association games** scheduled to be played on Wednesday, December 10th through Saturday, December 13th.

Specifically, you will predict the **temperature outside of the arena at the start of the game** and the **winning team** for each game.

You will receive a **$0.05 bonus** from MTurk every time you correctly predict the winner of a game.

Figure A1 61. Experiment 15: Temperature + Winner condition predictions.

This is a list of the 10 games scheduled to be played on Wednesday, December 10th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given the number of games they have won and lost so far this season. All records are up to date as of Wednesday, December 10th.

For each game, please predict the **temperature outside of the arena at the start of the game** and the **winning team**.

You will receive a **$0.05 bonus** from MTurk every time you correctly predict the winner of a game.

Wednesday, December 10th, 2014 at 7:00 pm

Los Angeles Clippers (15 wins, 5 losses) @ **Indiana Pacers** (7 wins, 14 losses)

If you correctly predict the winner of this game, you will earn **$0.05**

What will be the temperature outside of the arena at the start of the game?

Outdoor temperature (in Fahrenheit)

Who will win this game?

Los Angeles Clippers

Indiana Pacers

Experiment 16

Table A1 16. Experiment 16 design.

Predictions	30 National Hockey League games played on December 11th (10 games), December 12th (4 games), December 13th (13 games), and December 14th (3 games).
Run Date	December 11th, 2014
Conditions	Winner, Score + Winner, Saves + Winner, Temperature + Winner
Record information	Wins, losses
Measures in the example that are NOT included in this experiment	· Prediction strategy
Measures NOT in the example that ARE included in this experiment	· Base rates · How confusing were the instructions in the survey
Other deviations from the example format	· Participants were paid 75 cents for completing the study. · After making their predictions, participants in all conditions revisited each game and said how many times each team would win if they were to play that exact game 100 times.

Figure A1 62. Experiment 16: Winner condition predictions.

This is a list of the 10 games scheduled to be played on Thursday, December 11th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given the number of games they have won and lost so far this season. The number of losses given includes both regulation losses and overtime losses. All records are up to date as of Thursday, December 11th.

For each game, please predict the **winning team**.

You will receive a **$0.05 bonus** from MTurk every time you correctly predict the winner of a game.

Thursday, December 11th, 2014 at 7:00 pm

Calgary Flames (17 wins, 12 losses) @ **Buffalo Sabres** (10 wins, 18 losses)

If you correctly predict the winner of this game, you will earn **$0.05**

Who will win this game?

Calgary Flames ○ Buffalo Sabres ○

Figure A1 63. Experiment 16: Score + Winner condition predictions.

This is a list of the 10 games scheduled to be played on Thursday, December 11th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given the number of games they have won and lost so far this season. The number of losses given includes both regulation losses and overtime losses. All records are up to date as of Thursday, December 11th.

For each game, please predict the **final score** and the **winning team**.

You will receive a **$0.05 bonus** from MTurk every time you correctly predict the winner of a game.

Thursday, December 11th, 2014 at 7:00 pm

Calgary Flames (17 wins, 12 losses) @ **Buffalo Sabres** (10 wins, 18 losses)

If you correctly predict the winner of this game, you will earn **$0.05**

What will the final score of this game be?

How many points will the **Calgary Flames** score?

How many points will the **Buffalo Sabres** score?

Who will win this game?

Calgary Flames

Buffalo Sabres

Figure A1 64. Experiment 16: Saves + Winner condition instructions.

In this portion of the survey, you will predict the outcomes of the **30 National Hockey League games** scheduled to be played on Thursday, December 11th through Sunday, December 14th.

Specifically, you will predict the **number of saves each team will get** and the **winning team** for each game.

In ice hockey, a **save** occurs when the puck is shot towards the net but is blocked by the goaltender. In other words, a team gets a save when their goalie stops the puck from entering their net, preventing the opposing team from scoring a goal.

You will receive a **$0.05 bonus** from MTurk every time you correctly predict the winner of a game.

Figure A1 65. Experiment 16: Saves + Winner condition predictions.

This is a list of the 10 games scheduled to be played on Thursday, December 11th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given the number of games they have won and lost so far this season. The number of losses given includes both regulation losses and overtime losses. All records are up to date as of Thursday, December 11th.

For each game, please predict the **number of saves each team will get** and the **winning team**.

In ice hockey, a **save** occurs when the puck is shot towards the net but is blocked by the goaltender. In other words, a team gets a save when their goalie stops the puck from entering their net, preventing the opposing team from scoring a goal.

You will receive a **$0.05 bonus** from MTurk every time you correctly predict the winner of a game.

Thursday, December 11th, 2014 at 7:00 pm

Calgary Flames (17 wins, 12 losses) @ **Buffalo Sabres** (10 wins, 18 losses)

If you correctly predict the winner of this game, you will earn **$0.05**

How many saves will each team get?

How many saves will the **Calgary Flames** get?

How many saves will the **Buffalo Sabres** get?

Who will win this game?

Calgary Flames

Buffalo Sabres

Figure A1 66. Experiment 16: Crowd + Winner condition instructions.

In this portion of the survey, you will predict the outcomes of the **30 National Hockey League games** scheduled to be played on Thursday, December 11th through Sunday, December 14th.

Specifically, you will predict the **% of U.S. citizens in the crowd** at the arena and the **winning team** for each game.

You will receive a **$0.05 bonus** from MTurk every time you correctly predict the winner of a game.

Figure A1 67. Experiment 16: Crowd + Winner condition predictions.

This is a list of the 10 games scheduled to be played on Thursday, December 11th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given the number of games they have won and lost so far this season. The number of losses given includes both regulation losses and overtime losses. All records are up to date as of Thursday, December 11th.

For each game, please predict the **% of U.S. citizens in the crowd** at the arena and the **winning team**.

You will receive a **$0.05 bonus** from MTurk every time you correctly predict the winner of a game.

Thursday, December 11th, 2014 at 7:00 pm

Calgary Flames (17 wins, 12 losses) @ **Buffalo Sabres** (10 wins, 18 losses)

If you correctly predict the winner of this game, you will earn **$0.05**

What percentage of the crowd at the arena will be U.S. citizens?

% of U.S. citizens in the crowd (Enter a number between 0 and 100)

Who will win this game?

Calgary Flames

Buffalo Sabres

Figure A1 68. Experiment 16: Base rates (all conditions).

This is a list of the 10 games scheduled to be played on Thursday, December 11th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given the number of games they have won and lost so far this season. The number of losses given includes both regulation losses and overtime losses. All records are up to date as of Thursday, December 11th.

For each game, we will ask you to **imagine that the two teams played <u>that exact game</u> 100 times**.

What we mean by "that exact game" is that each of the 100 times the game is played, the game would begin with the <u>exact same starting conditions as the actual game</u>.

For example, the location and home team, the win/loss records of each team, the player lineup, player injuries, etc. <u>would all be the same at the beginning of each of the 100 games as they are at the beginning of the actual game</u>.

For each game, we will ask you to tell us **how many times you think each team would win** if that exact game were played 100 times.

Thursday, December 11th, 2014 at 7:00 pm

Calgary Flames (17 wins, 12 losses) @ **Buffalo Sabres** (10 wins, 18 losses)

Imagine these two teams played <u>this exact game</u> 100 times.

[0] How many games (out of 100) would the **Calgary Flames** win?

[0] How many games (out of 100) would the **Buffalo Sabres** win?

Experiment 17

Table A1 17. Experiment 17 design.

Predictions	31 National Hockey League games played on January 17^{th} (12 games), January 18^{th} (4 games), January 19^{th} (7 games), and January 20^{th} (8 games).
Run Date	January 17^{th}, 2015
Conditions	Winner, Score + Winner, Temperature + Winner, July 4^{th} + Winner
Record information	Wins, losses
Measures in the example that are NOT included in this experiment	· Prediction strategy · Global and local considerations
Measures NOT in the example that ARE included in this experiment	· "This Time" and "Usually" considerations · Base rates · How confusing were the instructions in the survey
Other deviations from the example format	· Participants were paid 75 cents for completing the study. · Each prediction was displayed on its own page individually instead of grouping predictions by day. · After making their predictions, participants in all conditions revisited each game and said how many times each team would win if they were to play that exact game 100 times.

Figure A1 69. Experiment 17: Winner condition predictions.

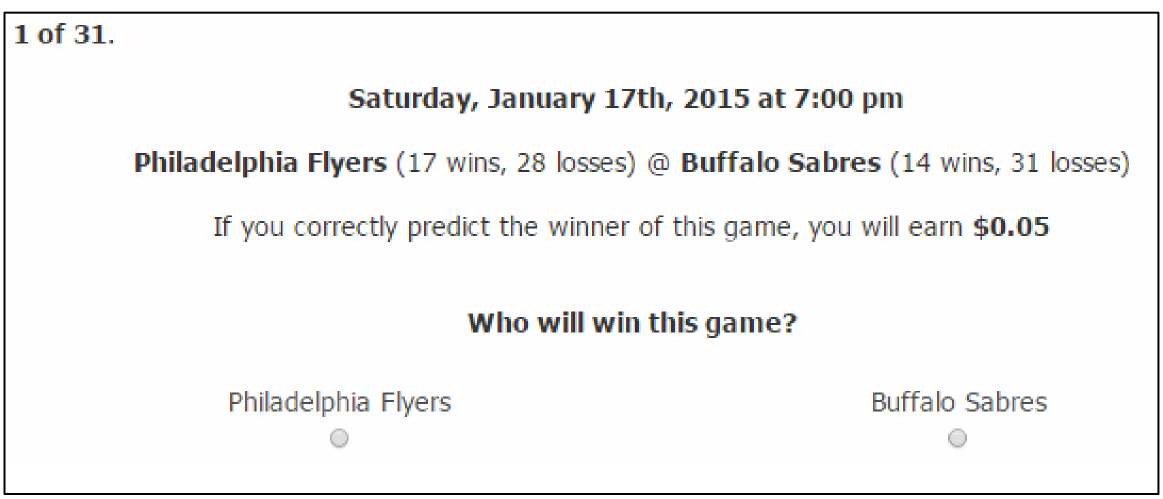
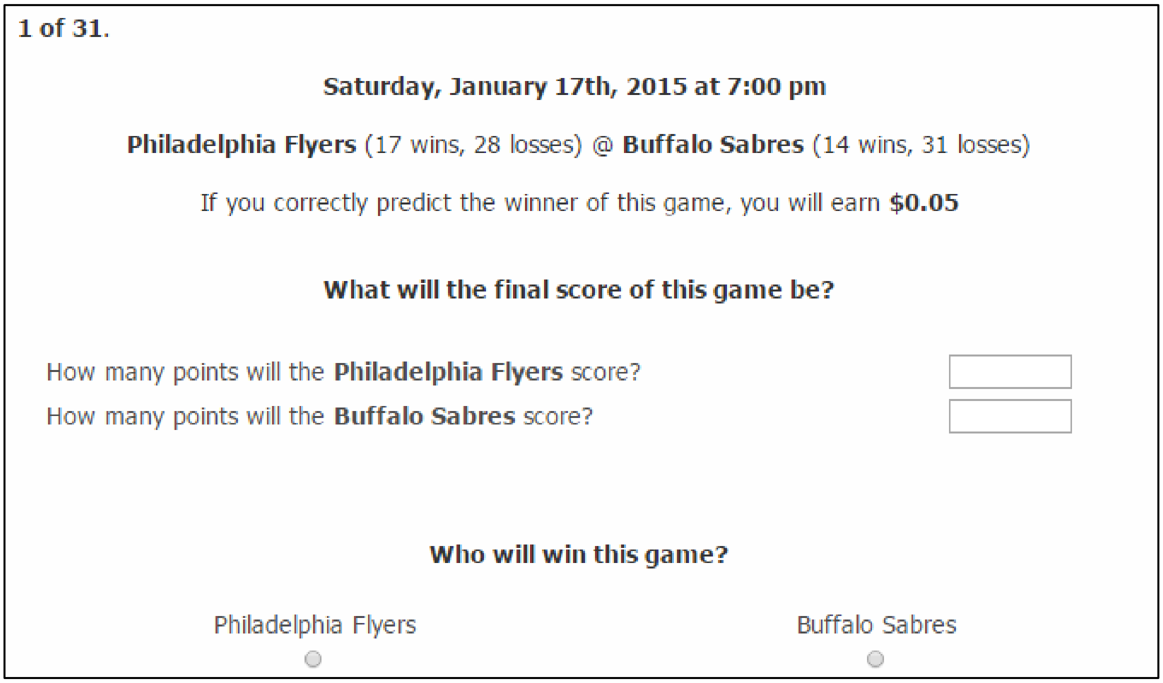


Figure A1 70. Experiment 17: Score + Winner condition predictions.


1 of 31.

Saturday, January 17th, 2015 at 7:00 pm

Philadelphia Flyers (17 wins, 28 losses) @ **Buffalo Sabres** (14 wins, 31 losses)

If you correctly predict the winner of this game, you will earn **$0.05**

What will the final score of this game be?

How many points will the **Philadelphia Flyers** score?

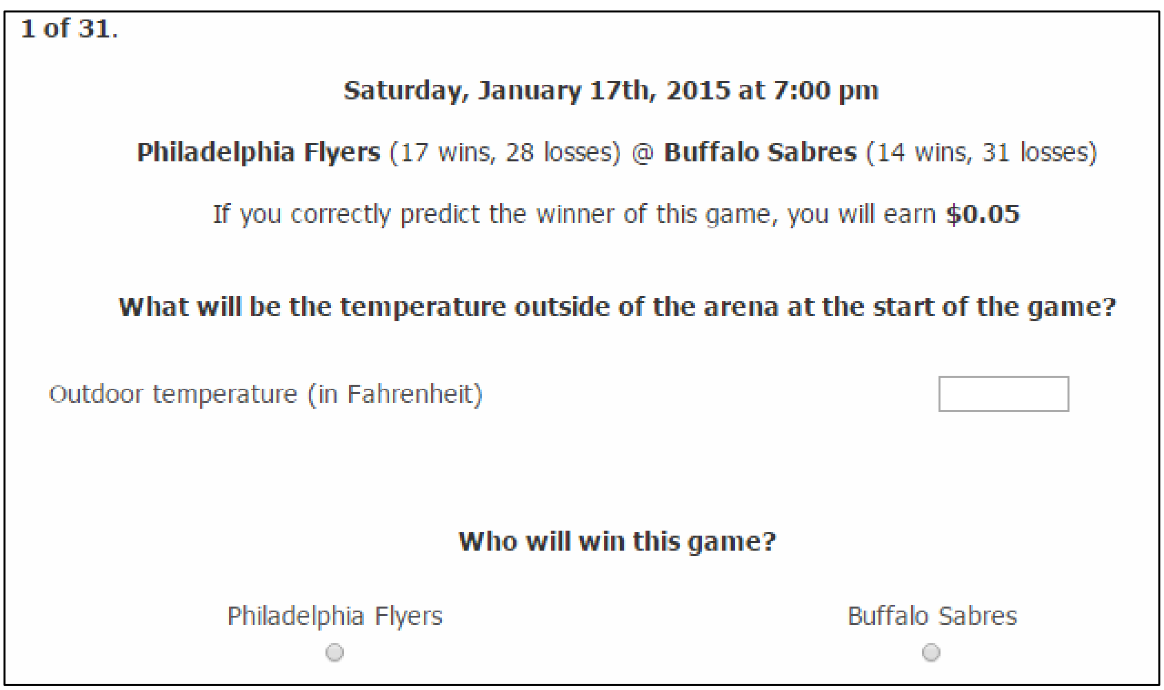
How many points will the **Buffalo Sabres** score?

Who will win this game?

Philadelphia Flyers

Buffalo Sabres

Figure A1 71. Experiment 17: Temperature + Winner condition predictions.


1 of 31.

Saturday, January 17th, 2015 at 7:00 pm

Philadelphia Flyers (17 wins, 28 losses) @ **Buffalo Sabres** (14 wins, 31 losses)

If you correctly predict the winner of this game, you will earn **$0.05**

What will be the temperature outside of the arena at the start of the game?

Outdoor temperature (in Fahrenheit)

Who will win this game?

Philadelphia Flyers

Buffalo Sabres

Figure A1 72. Experiment 17: July 4th + Winner condition instructions.

In this portion of the survey, you will predict the outcomes of the **31 National Hockey League games** scheduled to be played today, Saturday January 17th through Tuesday January 20th.

For each game, we will show you the visiting team (listed first) and the home team (listed second). We will also give you the number of games each team has won and lost so far this season. Please note that the number of losses given includes both regulation losses and overtime losses. All records are up to date as of today, Saturday January 17th.

Your task is to make two predictions for each game:

- First you will predict the **high temperature in the city where the game will take place on July 4th, 2015**.
- Then you will predict **which team will win** the game.

You will receive a **$0.05 bonus** from MTurk every time you correctly predict the winner of a game.

Figure A1 73. Experiment 17: July 4th + Winner condition predictions.

1 of 31.

Saturday, January 17th, 2015 at 7:00 pm

Philadelphia Flyers (17 wins, 28 losses) @ **Buffalo Sabres** (14 wins, 31 losses)

If you correctly predict the winner of this game, you will earn **$0.05**

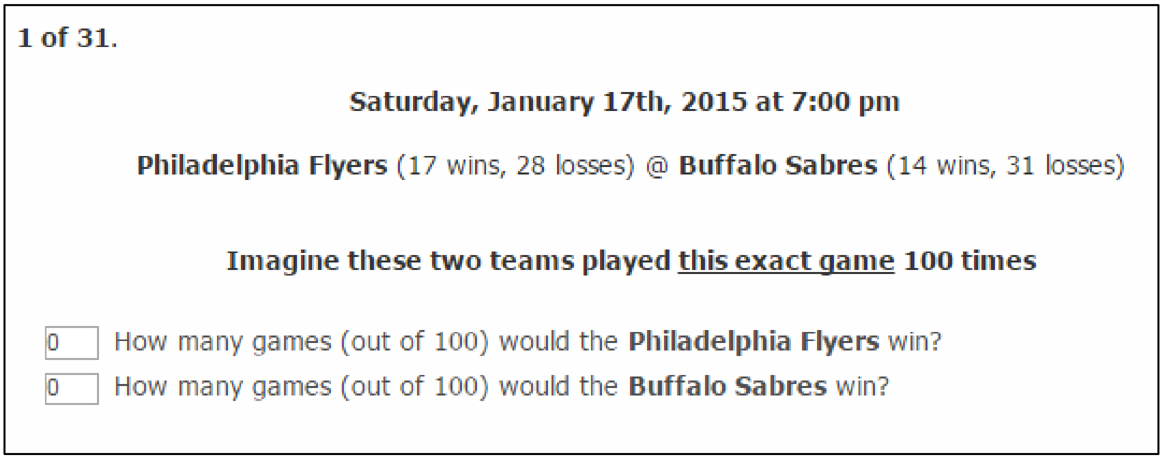
What will be the high temperature in Buffalo, New York on July 4th, 2015?

High temperature (in Fahrenheit)

Who will win this game?

Philadelphia Flyers　　　Buffalo Sabres

Figure A1 74. Experiment 17: Base rates (all conditions).



1 of 31.

Saturday, January 17th, 2015 at 7:00 pm

Philadelphia Flyers (17 wins, 28 losses) @ **Buffalo Sabres** (14 wins, 31 losses)

Imagine these two teams played <u>this exact game</u> 100 times

0 How many games (out of 100) would the **Philadelphia Flyers** win?

0 How many games (out of 100) would the **Buffalo Sabres** win?

Experiment 18

Experiment 18 is an exact replication of Experiment 17 except using NBA games instead of NHL games.

Table A1 18. Experiment 18 design.

Predictions	27 National Basketball Association games played on January 19th (9 games), January 20th (2 games), January 21st (12 games), and January 22nd (4 games).
Run Date	January 19th, 2015
Conditions	Winner, Score + Winner, Temperature + Winner, July 4th + Winner
Record information	Wins, losses
Measures in the example that are NOT included in this experiment	· Prediction strategy · Global and local considerations
Measures NOT in the example that ARE included in this experiment	· "This Time" and "Usually" considerations · Base rates · How confusing were the instructions in the survey
Other deviations from the example format	· Participants were paid 75 cents for completing the study. · Each prediction was displayed on its' own page individually instead of grouping by day. · After making their predictions, participants in all conditions revisited each game and said how many times each team would win if they were to play that exact game 100 times.

Experiment 19

Table A1 19. Experiment 19 design.

Predictions	31 National Hockey League games played on January 29th (11 games), January 30th (5 games), January 31st (11 games), and February 1st (4 games).
Run Date	January 19th, 2015
Conditions	Winner, Score + Winner
Record information	Wins, losses
Measures in the example that are NOT included in this experiment	· Prediction strategy · Global and local considerations
Measures NOT in the example that ARE included in this experiment	· "This Time" and "Usually" considerations · Base rates · How confusing were the instructions in the survey
Other deviations from the example format	· Each prediction was displayed on its' own page individually instead of grouping by day. · Participants were told at the beginning of the survey that some games would be worth 5-cents and some games would be worth 20-cents for correct winner predictions. Before making any predictions, they had to pass a comprehension check to show they understood the bonus scheme. · The 5-cent games and 20-cent games alternated and which games were worth the 5 cents and which were worth 20 cents was randomized between subjects. · Participants gave self-report measures (e.g., motivation and confidence) separately for the 5-cent and 20-cent games. · After making their predictions, participants in all conditions revisited each game and said how many times each team would win if they were to play that exact game 100 times.

Figure A1 75. Experiment 19: Bonus instructions.

In this survey, **some of the games will be worth more than others**.

For some games, you will earn a **$0.05** bonus if you correctly predict which team will win the game.
For other games, you will earn a **$0.20** bonus if you correctly predict which team will win the game.

We will tell you how much each game is worth before you make your prediction. To ensure you understand the instructions, please answer the following questions:

How much is the smaller bonus?

How much is the larger bonus?

Figure A1 76. Experiment 19: Winner condition predictions (small bonus).

1 of 31.

Thursday, January 29th, 2015 at 7:00 pm

Boston Bruins (25 wins, 23 losses) @ **New York Islanders** (32 wins, 15 losses)

If you correctly predict the winner of this game,you will earn:

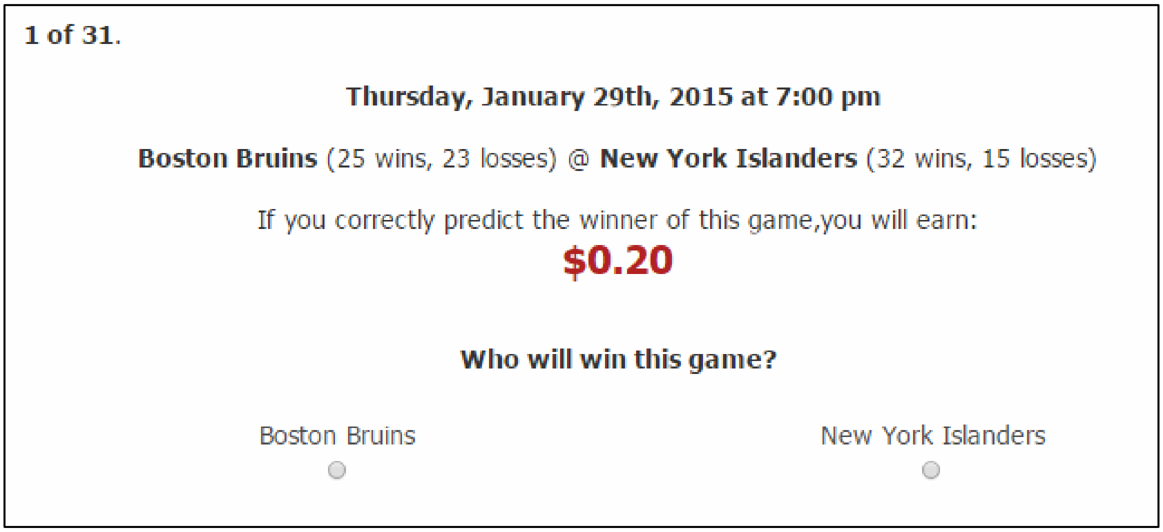
$0.05

Who will win this game?

Boston Bruins

New York Islanders

Figure A1 77. Experiment 19: Winner condition predictions (large bonus).



1 of 31.

Thursday, January 29th, 2015 at 7:00 pm

Boston Bruins (25 wins, 23 losses) @ **New York Islanders** (32 wins, 15 losses)

If you correctly predict the winner of this game,you will earn:

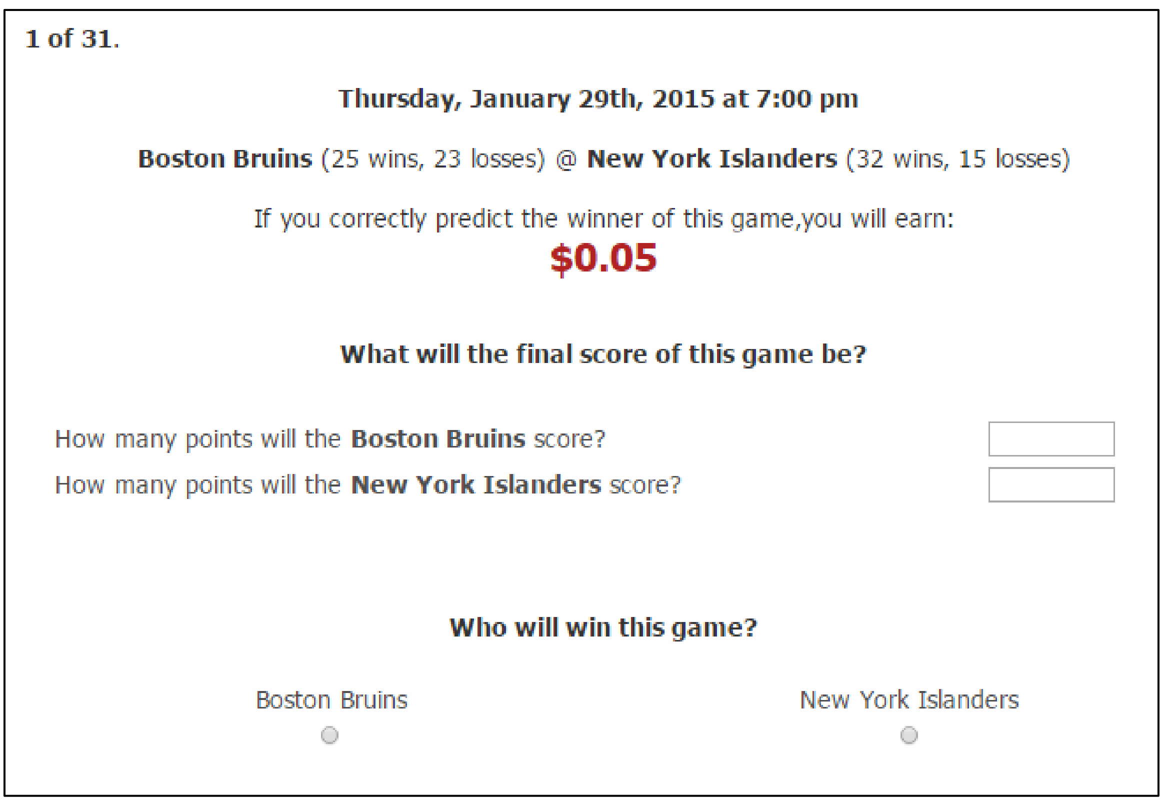
$0.20

Who will win this game?

Boston Bruins

New York Islanders

Figure A1 78. Experiment 19: Score + Winner condition predictions (small bonus).



1 of 31.

Thursday, January 29th, 2015 at 7:00 pm

Boston Bruins (25 wins, 23 losses) @ **New York Islanders** (32 wins, 15 losses)

If you correctly predict the winner of this game,you will earn:

$0.05

What will the final score of this game be?

How many points will the **Boston Bruins** score?

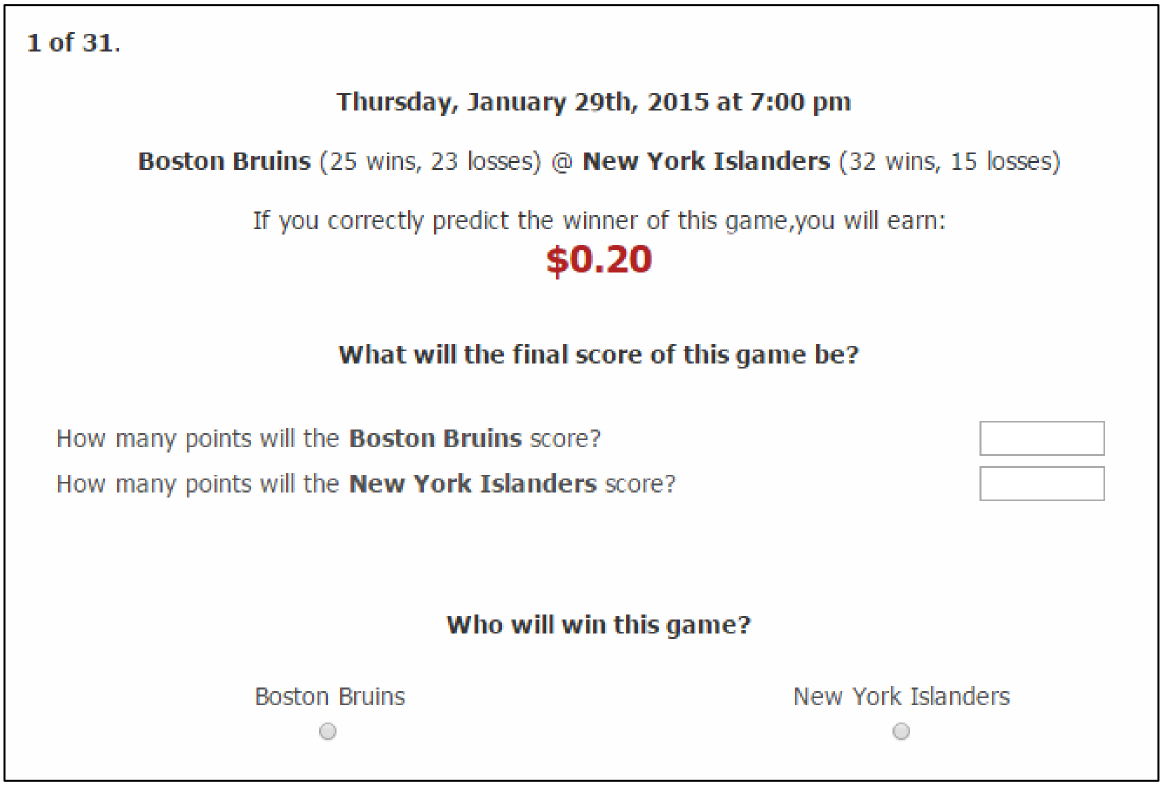
How many points will the **New York Islanders** score?

Who will win this game?

Boston Bruins

New York Islanders

Figure A1 79. Experiment 19: Score + Winner condition predictions (large bonus).


1 of 31.

Thursday, January 29th, 2015 at 7:00 pm

Boston Bruins (25 wins, 23 losses) @ **New York Islanders** (32 wins, 15 losses)

If you correctly predict the winner of this game,you will earn:
$0.20

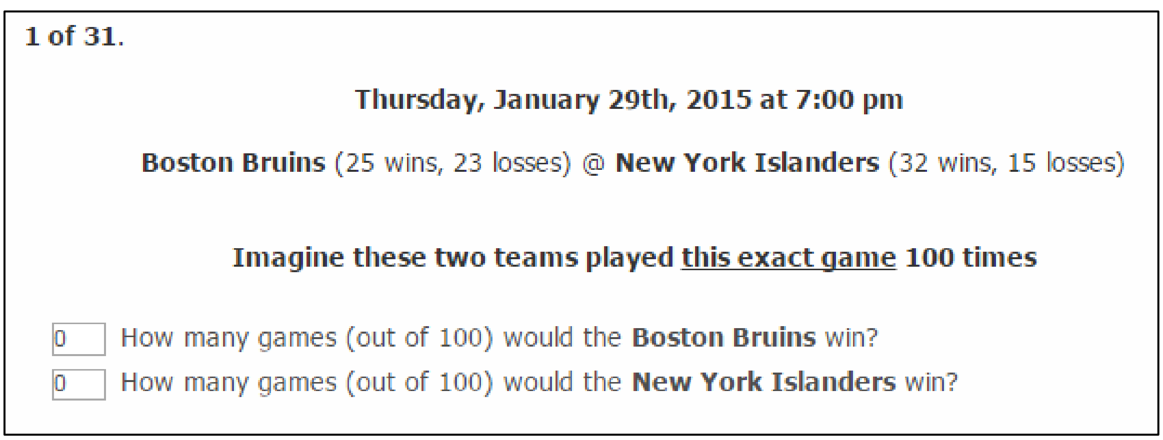
What will the final score of this game be?

How many points will the **Boston Bruins** score?
How many points will the **New York Islanders** score?

Who will win this game?

Boston Bruins
New York Islanders

Figure A1 80. Experiment 19: Base rates (all conditions).


1 of 31.

Thursday, January 29th, 2015 at 7:00 pm

Boston Bruins (25 wins, 23 losses) @ **New York Islanders** (32 wins, 15 losses)

Imagine these two teams played <u>this exact game</u> 100 times

0 How many games (out of 100) would the **Boston Bruins** win?
0 How many games (out of 100) would the **New York Islanders** win?

Excluded Experiments

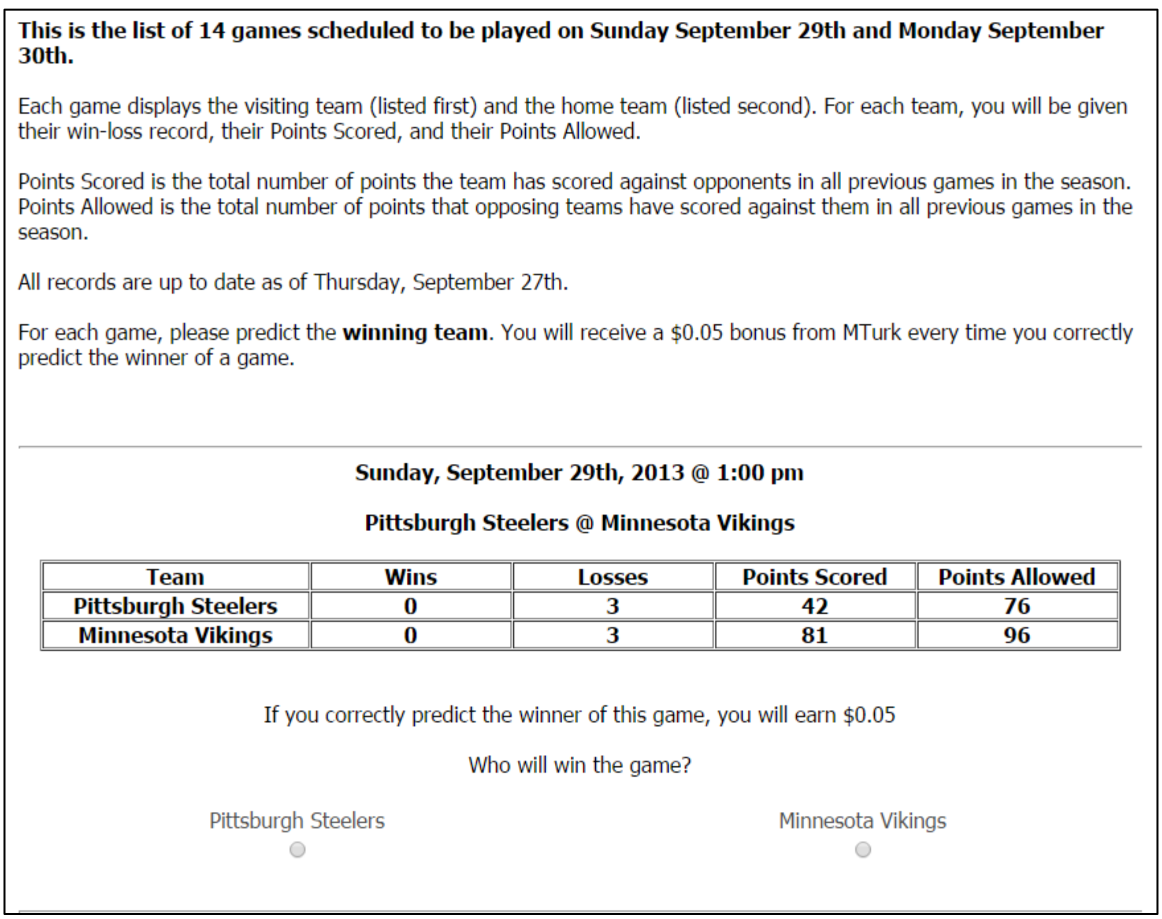
We also ran 8 additional experiments in which we gave participants each team's "Points Scored" (the total number of points scored by that team so far that season) and "Points Allowed" (the total number of points scored against that team so far that season) for football and hockey games, and each team's "Average Points Scored" (the average number of points scored by that team per game so far that season) and "Average Points Allowed" (the average number of points scored against that team per game so far that season) for basketball games. However, we chose not to include these experiments in the main analyses because we were worried that differences between prediction conditions in these studies (namely, between Winner and Score + Winner) may have arisen because people who are asked about winners only look at the win/loss records and people who are asked about scores only look at the points scored or average points scored data. It should be noted that the effects we report are stronger when we include the data from these 8 experiments.

Experiment E1

Table A1 20. Experiment E1 design.

Predictions	14 National Football League games played on September 29th (13 games) and September 30th (1 game) in 2013.
Run Date	September 27th, 2013
Conditions	Winner, Score + Winner, Points + Winner
Record information	Wins, losses, points scored, points allowed
Measures in the example that are NOT included in this experiment	· Self-reported following and knowledge · Which sports they are interested in being contacted about.
Other deviations from the example format	· All games were displayed on a single page

Figure A1 81. Experiment E1: Winner condition predictions.



This is the list of 14 games scheduled to be played on Sunday September 29th and Monday September 30th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Points Scored, and their Points Allowed.

Points Scored is the total number of points the team has scored against opponents in all previous games in the season. Points Allowed is the total number of points that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Thursday, September 27th.

For each game, please predict the **winning team**. You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Sunday, September 29th, 2013 @ 1:00 pm

Pittsburgh Steelers @ Minnesota Vikings

Team	Wins	Losses	Points Scored	Points Allowed
Pittsburgh Steelers	0	3	42	76
Minnesota Vikings	0	3	81	96

If you correctly predict the winner of this game, you will earn $0.05

Who will win the game?

Pittsburgh Steelers

Minnesota Vikings

Figure A1 82. Experiment E1: Score + Winner condition predictions.

This is the list of 14 games scheduled to be played on Sunday September 29th and Monday September 30th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Points Scored, and their Points Allowed.

Points Scored is the total number of points the team has scored against opponents in all previous games in the season. Points Allowed is the total number of points that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Thursday, September 27th.

For each game, please predict the **final score** and **winning team**. You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Sunday, September 29th, 2013 @ 1:00 pm

Pittsburgh Steelers @ Minnesota Vikings

Team	Wins	Losses	Points Scored	Points Allowed
Pittsburgh Steelers	0	3	42	76
Minnesota Vikings	0	3	81	96

If you correctly predict the winner of this game, you will earn $0.05

How many points will the **Pittsburgh Steelers** score?

How many points will the **Minnesota Vikings** score?

Who will win the game?

Pittsburgh Steelers

Minnesota Vikings

Figure A1 83. Experiment E1: Points + Winner condition instructions.

In this survey, you will predict the outcomes of the 14 National Football League games scheduled to be played on Sunday September 29th and Monday September 30th.

Specifically, you will predict the **total number of points scored by both teams** and **winning team** for each game.

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Figure A1 84. Experiment E1: Points + Winner condition predictions.

This is the list of 14 games scheduled to be played on Sunday September 29th and Monday September 30th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Points Scored, and their Points Allowed.

Points Scored is the total number of points the team has scored against opponents in all previous games in the season. Points Allowed is the total number of points that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Thursday, September 27th.

For each game, please predict the **total number of points scored** and **winning team**. You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Sunday, September 29th, 2013 @ 1:00 pm

Pittsburgh Steelers @ Minnesota Vikings

Team	Wins	Losses	Points Scored	Points Allowed
Pittsburgh Steelers	0	3	42	76
Minnesota Vikings	0	3	81	96

If you correctly predict the winner of this game, you will earn $0.05

How many points will be scored during this game?

Who will win the game?

Pittsburgh Steelers

Minnesota Vikings

Experiment E2

The format of this experiment is an exact replication of Experiment E1.

Table A1 21. Experiment E2 design.

Predictions	13 National Football League games played on October 24th (1 game), October 27th (11 games), and October 28th (1 game) in 2013.
Run Date	October 24th, 2013
Conditions	Winner, Score + Winner, Points + Winner
Record information	Wins, losses, points scored, points allowed
Measures in the example that are NOT included in this experiment	· Self-reported following and knowledge · Which sports they are interested in being contacted about.
Other deviations from the example format	· All games were displayed on a single page

Experiment E3

The format of this experiment is an exact replication of Experiments E1 and E2.

Table A1 22. Experiment E3 design.

Predictions	13 National Football League games played on October 31st (1 game), November 3rd (11 games), November 4th (1 game) in 2013.
Run Date	October 30th, 2013
Conditions	Winner, Score + Winner, Points + Winner
Record information	Wins, losses, points scored, points allowed
Measures in the example that are NOT included in this experiment	· Self-reported following and knowledge · Which sports they are interested in being contacted about.
Other deviations from the example format	· All games were displayed on a single page · Each of the 8 measured knowledge questions was displayed on a separate page.

Experiment E4

In this experiment we manipulated the sport (basketball vs. hockey) between subjects.

Table A1 23. Experiment E4 design.

Predictions	33 National Basketball Association games played on November 29th (13 games), November 30th (7 games), December 1st (8 games), and December 2nd (5 games) in 2013. 30 National Hockey League games played on November 29th (12 games), November 30th (11 games), December 1st (3 games), December 2nd (4 games) in 2013.
Run Date	November 26th, 2013
Conditions	Predictions (Winner vs. Score + Winner) X Sport (NBA vs. NHL)
Record information	Wins, losses, average points scored (NBA), average points allowed (NBA), goals scored (NHL), goals allowed (NHL)
Measures in the example that are NOT included in this experiment	· Self-reported following and knowledge.
Other deviations from the example format	· Each of the 8 measured knowledge questions was displayed on a separate page.

Figure A1 85. Experiment E4: Winner condition predictions (NBA).

This is the list of the 13 games scheduled to be played on Friday November 29th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Average Points Scored, and their Average Points Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season.
- **Average Points Scored** is the average number of points the team has scored against opponents in all previous games in the season.
- **Average Points Allowed** is the average number of points that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Tuesday, November 26th.

For each game, please predict the **winning team**. You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Friday, November 29th, 2013 @ 7:00 pm

Milwaukee Bucks @ Charlotte Bobcats

Team	Wins	Losses	Average Points Scored	Average Points Allowed
Milwaukee Bucks	2	11	89.9	100.2
Charlotte Bobcats	7	8	89.4	91.9

If you correctly predict the winner of this game, you will earn $0.05

Who will win the game?

Milwaukee Bucks

Charlotte Bobcats

Figure A1 86. Experiment E4: Score + Winner condition predictions (NBA).

This is the list of the 13 games scheduled to be played on Friday November 29th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Average Points Scored, and their Average Points Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season.
- **Average Points Scored** is the average number of points the team has scored against opponents in all previous games in the season.
- **Average Points Allowed** is the average number of points that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Tuesday, November 26th.

For each game, please predict the **final score** and **winning team**. You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Friday, November 29th, 2013 @ 7:00 pm

Milwaukee Bucks @ Charlotte Bobcats

Team	Wins	Losses	Average Points Scored	Average Points Allowed
Milwaukee Bucks	2	11	89.9	100.2
Charlotte Bobcats	7	8	89.4	91.9

If you correctly predict the winner of this game, you will earn $0.05

How many points will the **Milwaukee Bucks** score?

How many points will the **Charlotte Bobcats** score?

Who will win the game?

Milwaukee Bucks

Charlotte Bobcats

Figure A1 87. Experiment E4: Winner condition predictions (NHL).

This is the list of the 12 games scheduled to be played on Friday November 29th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Goals Scored, and their Goals Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season, including Overtime Losses and Shootout Losses.
- **Goals Scored** is the total number of goals the team has scored against opponents in all previous games in the season.
- **Goals Allowed** is the total number of goals that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Tuesday, November 26th.

For each game, please predict the **winning team**. You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Friday, November 29th, 2013 @ 11:30 am

Winnipeg Jets @ Philadelphia Flyers

Team	Wins	Losses	Goals Scored	Goals Allowed
Winnipeg Jets	**11**	**15**	**69**	**76**
Philadelphia Flyers	**10**	**13**	**50**	**56**

If you correctly predict the winner of this game, you will earn $0.05

Who will win the game?

Winnipeg Jets

Philadelphia Flyers

Figure A1 88. Experiment E4: Score + Winner condition predictions (NHL).

This is the list of the 12 games scheduled to be played on Friday November 29th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Goals Scored, and their Goals Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season, including Overtime Losses and Shootout Losses.
- **Goals Scored** is the total number of goals the team has scored against opponents in all previous games in the season.
- **Goals Allowed** is the total number of goals that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Tuesday, November 26th.

For each game, please predict the **final score** and **winning team**. You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Friday, November 29th, 2013 @ 11:30 am

Winnipeg Jets @ Philadelphia Flyers

Team	Wins	Losses	Goals Scored	Goals Allowed
Winnipeg Jets	11	15	69	76
Philadelphia Flyers	10	13	50	56

If you correctly predict the winner of this game, you will earn $0.05

How many points will the **Winnipeg Jets** score?

How many points will the **Philadelphia Flyers** score?

Who will win the game?

Winnipeg Jets

Philadelphia Flyers

Experiment E5

Table A1 24. Experiment E5 design.

Predictions	32 National Hockey League games played on December 27th (10 games), December 28th (8 games), December 29th (10 games), and December 30th (4 games) in 2013.
Run Date	December 26th, 2013
Conditions	Winner, Score + Winner, Crowd + Winner
Record information	Wins, losses, goals scored, goals allowed

Figure A1 89. Experiment E5: Winner condition predictions.

This is the list of the 10 games scheduled to be played on Friday December 27th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Goals Scored, and their Goals Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season, including Overtime Losses and Shootout Losses.
- **Goals Scored** is the total number of goals the team has scored against opponents in all previous games in the season.
- **Goals Allowed** is the total number of goals that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Thursday, December 26th.

For each game, please predict the **winning team**. You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Friday, December 27th, 2013 @ 7:00 pm

Buffalo Sabres @ Toronto Maple Leafs

Team	Wins	Losses	Goals Scored	Goals Allowed
Buffalo Sabres	10	27	66	105
Toronto Maple Leafs	18	21	106	113

If you correctly predict the winner of this game, you will earn $0.05

Who will win the game?

Buffalo Sabres

Toronto Maple Leafs

Figure A1 90. Experiment E5: Score + Winner condition predictions.

This is the list of the 10 games scheduled to be played on Friday December 27th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Goals Scored, and their Goals Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season, including Overtime Losses and Shootout Losses.
- **Goals Scored** is the total number of goals the team has scored against opponents in all previous games in the season.
- **Goals Allowed** is the total number of goals that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Thursday, December 26th.

For each game, please predict the **final score** and **winning team**. You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Friday, December 27th, 2013 @ 7:00 pm

Buffalo Sabres @ Toronto Maple Leafs

Team	Wins	Losses	Goals Scored	Goals Allowed
Buffalo Sabres	10	27	66	105
Toronto Maple Leafs	18	21	106	113

If you correctly predict the winner of this game, you will earn $0.05

How many points will the **Buffalo Sabres** score?

How many points will the **Toronto Maple Leafs** score?

Who will win the game?

Buffalo Sabres

Toronto Maple Leafs

Figure A1 91. Experiment E5: Crowd + Winner condition instructions.

In this survey, you will predict the outcomes of the **32 National Hockey League games** scheduled to be played on Friday December 27th through Monday December 30th.

Specifically, you will predict the **% of U.S. citizens in the crowd** at the arena and the **winning team** for each game.

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Figure A1 92. Experiment E5: Crowd + Winner condition predictions.

This is the list of the 10 games scheduled to be played on Friday December 27th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Goals Scored, and their Goals Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season, including Overtime Losses and Shootout Losses.
- **Goals Scored** is the total number of goals the team has scored against opponents in all previous games in the season.
- **Goals Allowed** is the total number of goals that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Thursday, December 26th.

For each game, please predict the **% of U.S. citizens in the crowd** at the arena and **winning team**. You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Friday, December 27th, 2013 @ 7:00 pm

Buffalo Sabres @ Toronto Maple Leafs

Team	Wins	Losses	Goals Scored	Goals Allowed
Buffalo Sabres	**10**	**27**	**66**	**105**
Toronto Maple Leafs	**18**	**21**	**106**	**113**

If you correctly predict the winner of this game, you will earn $0.05

What percentage of the crowd will be U.S. citizens? (Enter a number between 0 and 100)

Who will win the game?

Buffalo Sabres

Toronto Maple Leafs

Experiment E6

Table A1 25. Experiment E6 design.

Predictions	26 National Hockey League games played on February 6th (11 games), February 7th (5 games), and February 8th (10 games) in 2014.
Run Date	February 6th, 2014
Conditions	Predictions (Winner vs. Score + Winner) X No majority winner prediction vs. Majority winner prediction
Record information	Wins, losses, goals scored, goals allowed

Figure A1 93. Experiment E6: Winner condition predictions (no majority winner prediction).

This is the list of the 11 games scheduled to be played on Thursday February 6th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Goals Scored, and their Goals Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season, including Overtime Losses and Shootout Losses.
- **Goals Scored** is the total number of goals the team has scored against opponents in all previous games in the season.
- **Goals Allowed** is the total number of goals that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Thursday, February 6th.

For each game, please predict **which team will win** the game**.**

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Thursday, February 6th, 2014 @ 7:00 pm

Calgary Flames @ New York Islanders

Team	Wins	Losses	Goals Scored	Goals Allowed
Calgary Flames	21	35	132	175
New York Islanders	22	36	160	191

If you correctly predict the winner of this game, you will earn $0.05

Who will win this game?

Calgary Flames ○ New York Islanders ○

Figure A1 94. Experiment E6: Score + Winner condition predictions (no majority winner prediction).

This is the list of the 11 games scheduled to be played on Thursday February 6th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Goals Scored, and their Goals Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season, including Overtime Losses and Shootout Losses.
- **Goals Scored** is the total number of goals the team has scored against opponents in all previous games in the season.
- **Goals Allowed** is the total number of goals that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Thursday, February 6th.

For each game, please predict the **final score** of the game and **which team will win** the game**.**

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Thursday, February 6th, 2014 @ 7:00 pm

Calgary Flames @ New York Islanders

Team	Wins	Losses	Goals Scored	Goals Allowed
Calgary Flames	**21**	**35**	**132**	**175**
New York Islanders	**22**	**36**	**160**	**191**

If you correctly predict the winner of this game, you will earn $0.05

What will the final score of this game be?

How many points will the **Calgary Flames** score?

How many points will the **New York Islanders** score?

Who will win this game?

Calgary Flames

New York Islanders

Figure A1 95. Experiment E6: Winner condition instructions (with majority winner prediction).

In this survey, you will predict the outcomes of the **26 National Hockey League games** scheduled to be played on Thursday, February 6th through Saturday, February 8th.

Specifically, for each game you will predict **which team would win the most out of 101 games** and **which team will win the actual game**.

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Figure A1 96. Experiment E6: Winner condition predictions (with majority winner prediction).

This is the list of the 11 games scheduled to be played on Thursday February 6th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Goals Scored, and their Goals Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season, including Overtime Losses and Shootout Losses.
- **Goals Scored** is the total number of goals the team has scored against opponents in all previous games in the season.
- **Goals Allowed** is the total number of goals that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Thursday, February 6th.

For each game, please predict **which team would win the most out of 101 games** and **which team will win the actual game.**

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Thursday, February 6th, 2014 @ 7:00 pm

Calgary Flames @ New York Islanders

Team	Wins	Losses	Goals Scored	Goals Allowed
Calgary Flames	**21**	**35**	**132**	**175**
New York Islanders	**22**	**36**	**160**	**191**

If you correctly predict the winner of this game, you will earn $0.05

Imagine these teams played this game 101 times. Which team would win the majority of those games?

Calgary Flames　　New York Islanders

Who will win this game?

Calgary Flames　　New York Islanders

Figure A1 97. Experiment E6: Score + Winner condition instructions (with majority winner prediction).

In this survey, you will predict the outcomes of the **26 National Hockey League games** scheduled to be played on Thursday, February 6th through Saturday, February 8th.

Specifically, for each game you will predict **which team would win the most out of 101 games**, the **final score of the actual game,** and **which team will win the actual game**.

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Figure A1 98. Experiment E6: Score + Winner condition predictions (with majority winner prediction).

This is the list of the 11 games scheduled to be played on Thursday February 6th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Goals Scored, and their Goals Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season, including Overtime Losses and Shootout Losses.
- **Goals Scored** is the total number of goals the team has scored against opponents in all previous games in the season.
- **Goals Allowed** is the total number of goals that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Thursday, February 6th.

For each game, please predict **which team would win the most out of 101 games,** the **final score of the actual game**, and **which team will win the actual game.**

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Thursday, February 6th, 2014 @ 7:00 pm

Calgary Flames @ New York Islanders

Team	Wins	Losses	Goals Scored	Goals Allowed
Calgary Flames	21	35	132	175
New York Islanders	22	36	160	191

If you correctly predict the winner of this game, you will earn $0.05

Imagine these teams played this game 101 times. Which team would win the majority of those games?

Calgary Flames ○ New York Islanders ○

What will the final score of this game be?

How many points will the **Calgary Flames** score?

How many points will the **New York Islanders** score?

Who will win this game?

Calgary Flames ○ New York Islanders ○

Experiment E7

Table A1 26. Experiment E7 design.

Predictions	33 National Basketball Association games played on February 18th (9 games), February 19th (11 games), February 20th (3 games), and February 21st (10 games) in 2014.
Run Date	February 18th, 2014
Conditions	Predictions (Winner vs. Score + Winner) X No majority winner prediction vs. Majority winner prediction
Record information	Wins, losses, average points scored, average points allowed

Figure A1 99. Experiment E7: Winner condition predictions (no majority winner prediction).

This is the list of the 9 games scheduled to be played on Tuesday, February 18th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Average Points Scored, and their Average Points Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season.
- **Average Points Scored** is the average number of points the team has scored against opponents in all previous games in the season.
- **Average Points Allowed** is the average number of points that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Monday, February 17th.

or each game, please predict **which team will win** the game**.**

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Tuesday, February 18th, 2014 @ 7:00 pm

Cleveland Cavaliers @ Philadelphia 76ers

Team	Wins	Losses	Average Points Scored	Average Points Allowed
Cleveland Cavaliers	**20**	**33**	**96.7**	**102**
Philadelphia 76ers	**15**	**39**	**100.3**	**110.4**

If you correctly predict the winner of this game, you will earn $0.05

Who will win this game?

Cleveland Cavaliers ○ Philadelphia 76ers ○

Figure A1 100. Experiment E7: Score + Winner condition predictions (no majority winner prediction).

This is the list of the 9 games scheduled to be played on Tuesday, February 18th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Average Points Scored, and their Average Points Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season.
- **Average Points Scored** is the average number of points the team has scored against opponents in all previous games in the season.
- **Average Points Allowed** is the average number of points that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Monday, February 17th.

For each game, please predict the **final score** of the game and **which team will win** the game**.**

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Tuesday, February 18th, 2014 @ 7:00 pm

Cleveland Cavaliers @ Philadelphia 76ers

Team	Wins	Losses	Average Points Scored	Average Points Allowed
Cleveland Cavaliers	**20**	**33**	**96.7**	**102**
Philadelphia 76ers	**15**	**39**	**100.3**	**110.4**

If you correctly predict the winner of this game, you will earn $0.05

What will the final score of this game be?

How many points will the **Cleveland Cavaliers** score?

How many points will the **Philadelphia 76ers** score?

Who will win this game?

Cleveland Cavaliers

Philadelphia 76ers

Figure A1 101. Experiment E7: Winner condition predictions (with majority winner prediction).

This is the list of the 9 games scheduled to be played on Tuesday, February 18th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Average Points Scored, and their Average Points Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season.
- **Average Points Scored** is the average number of points the team has scored against opponents in all previous games in the season.
- **Average Points Allowed** is the average number of points that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Monday, February 17th.

For each game, please predict **which team would win the most out of 101 games** and **which team will win the actual game.**

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Tuesday, February 18th, 2014 @ 7:00 pm

Cleveland Cavaliers @ Philadelphia 76ers

Team	Wins	Losses	Average Points Scored	Average Points Allowed
Cleveland Cavaliers	**20**	**33**	**96.7**	**102**
Philadelphia 76ers	**15**	**39**	**100.3**	**110.4**

If you correctly predict the winner of this game, you will earn $0.05

Imagine these teams played this game 101 times. Which team would win the majority of those games?

Cleveland Cavaliers   Philadelphia 76ers

Who will win this game?

Cleveland Cavaliers   Philadelphia 76ers

Figure A1 102. Experiment E7: Score + Winner condition (with majority winner prediction).

This is the list of the 9 games scheduled to be played on Tuesday, February 18th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Average Points Scored, and their Average Points Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season.
- **Average Points Scored** is the average number of points the team has scored against opponents in all previous games in the season.
- **Average Points Allowed** is the average number of points that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Monday, February 17th.

For each game, please predict **which team would win the most out of 101 games,** the **final score of the actual game**, and **which team will win the actual game.**

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Tuesday, February 18th, 2014 @ 7:00 pm

Cleveland Cavaliers @ Philadelphia 76ers

Team	Wins	Losses	Average Points Scored	Average Points Allowed
Cleveland Cavaliers	20	33	96.7	102
Philadelphia 76ers	15	39	100.3	110.4

If you correctly predict the winner of this game, you will earn $0.05

Imagine these teams played this game 101 times. Which team would win the majority of those games?

Cleveland Cavaliers ○ Philadelphia 76ers ○

What will the final score of this game be?

How many points will the **Cleveland Cavaliers** score?

How many points will the **Philadelphia 76ers** score?

Who will win this game?

Cleveland Cavaliers ○ Philadelphia 76ers ○

Experiment E8

Table A1 27. Experiment E8 design.

Predictions	32 National Basketball Association games played on March 14th (10 games), March 15th (6 games), March 16th (9 games), and March 17th (9 games) in 2014.
Run Date	March 14th, 2014
Conditions	Winner, Score + Winner, Free Throws + Winner, Temperature + Winner
Record information	Wins, losses, average points scored, average points allowed

Figure A1 103. Experiment E8: Winner condition predictions.

This is the list of the 10 games scheduled to be played on Friday, March 14th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Average Points Scored, and their Average Points Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season.
- **Average Points Scored** is the average number of points the team has scored against opponents in all previous games in the season.
- **Average Points Allowed** is the average number of points that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Friday, March 14th.

For each game, please predict the **winning team.**

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Friday, March 14th, 2014 @ 7:00 pm

Washington Wizards @ Orlando Magic

Team	Wins	Losses	Average Points Scored	Average Points Allowed
Washington Wizards	33	31	100.5	99.9
Orlando Magic	19	47	97	102.2

If you correctly predict the winner of this game, you will earn $0.05

Who will win this game?

Washington Wizards ○ Orlando Magic ○

Figure A1 104. Experiment E8: Score + Winner condition predictions.

This is the list of the 10 games scheduled to be played on Friday, March 14th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Average Points Scored, and their Average Points Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season.
- **Average Points Scored** is the average number of points the team has scored against opponents in all previous games in the season.
- **Average Points Allowed** is the average number of points that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Friday, March 14th.

For each game, please predict the **final score** of the game and the **winning team.**

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Friday, March 14th, 2014 @ 7:00 pm

Washington Wizards @ Orlando Magic

Team	Wins	Losses	Average Points Scored	Average Points Allowed
Washington Wizards	33	31	100.5	99.9
Orlando Magic	19	47	97	102.2

If you correctly predict the winner of this game, you will earn $0.05

What will the final score of this game be?

How many points will the **Washington Wizards** score?

How many points will the **Orlando Magic** score?

Who will win this game?

Washington Wizards

Orlando Magic

Figure A1 105. Experiment E8: Free Throws + Winner condition instructions.

In this survey, you will predict the outcomes of the **32 National Basketball Association games** scheduled to be played on Friday, March 14th through Monday, March 17th.

Specifically, you will predict **how many free throws each team will attempt** and the **winning team** for each game.

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Figure A1 106. Experiment E8: Free Throws + Winner condition predictions.

This is the list of the 10 games scheduled to be played on Friday, March 14th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Average Points Scored, and their Average Points Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season.
- **Average Points Scored** is the average number of points the team has scored against opponents in all previous games in the season.
- **Average Points Allowed** is the average number of points that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Friday, March 14th.

For each game, please predict **how many free throws each team will attempt** and the **winning team.**

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Friday, March 14th, 2014 @ 7:00 pm

Washington Wizards @ Orlando Magic

Team	Wins	Losses	Average Points Scored	Average Points Allowed
Washington Wizards	**33**	**31**	**100.5**	**99.9**
Orlando Magic	**19**	**47**	**97**	**102.2**

If you correctly predict the winner of this game, you will earn $0.05

How many free throws will each team attempt?

How many free throws will the **Washington Wizards** attempt?

How many free throws will the **Orlando Magic** attempt?

Who will win this game?

Washington Wizards

Orlando Magic

Figure A1 107. Experiment E8: Temperature + Winner condition instructions.

In this survey, you will predict the outcomes of the **32 National Basketball Association games** scheduled to be played on Friday, March 14th through Monday, March 17th.

Specifically, you will predict the **temperature outside of the arena at the start of the game** and the **winning team** for each game.

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Figure A1 108. Experiment E8: Temperature + Winner condition predictions.

This is the list of the 10 games scheduled to be played on Friday, March 14th.

Each game displays the visiting team (listed first) and the home team (listed second). For each team, you will be given their win-loss record, their Average Points Scored, and their Average Points Allowed.

- **Wins** is the number of games the team has won so far this season.
- **Losses** is the number of games the team has lost so far this season.
- **Average Points Scored** is the average number of points the team has scored against opponents in all previous games in the season.
- **Average Points Allowed** is the average number of points that opposing teams have scored against them in all previous games in the season.

All records are up to date as of Friday, March 14th.

For each game, please predict the **outdoor temperature at the start of the game** and the **winning team.**

You will receive a $0.05 bonus from MTurk every time you correctly predict the winner of a game.

Friday, March 14th, 2014 @ 7:00 pm

Washington Wizards @ Orlando Magic

Team	Wins	Losses	Average Points Scored	Average Points Allowed
Washington Wizards	33	31	100.5	99.9
Orlando Magic	19	47	97	102.2

If you correctly predict the winner of this game, you will earn $0.05

What will be the temperature outside of the arena at the start of the game?

Outdoor temperature:
(in Fahrenheit)

Who will win this game?

Washington Wizards

Orlando Magic

APPENDIX A2: ADDITIONAL MEASURES

All additional measures were collected after participants made all of their predictions. The additional measures are reported in the order that they appeared in the corresponding experiments. Not all measures appeared in all experiments.

To account for both observed and unobserved differences between experiments, the means for each variable we report are mean-centered by experiment and added to the overall average for that measure across all experiments and conditions. All correlations are also based on these mean-centered values. Significance tests are based on fixed-effects linear models.

Finally, the analyses reported in this document are only based on data from the 19 experiments included in the paper. Furthermore, in all instances a participant's "prediction quality" is defined as the percentage of games where they predicted that the team favored by well-calibrated markets would win (see the "Prediction Quality" section of the main paper for more details).

Winning team probabilities / base rates (Experiments 7, 9, 11, 14-19)

On a separate page, immediately after making their predictions for all games, participants were given instructions informing them that they will be asked to report how likely each team was to win each game. Then on the following pages they were asked to imagine for each game that the two teams played that *exact same game* 100 times and to indicate how many times each team would win.

We included these questions because we wanted to explore whether people were thinking that the upcoming games would be different from games in the past (e.g., "I know that the Braves usually beat the Pirates, but I think this time will be different and the Pirates will win.”). If making detailed predictions changed people’s beliefs about which teams were typically more likely to win, then doing so should affect their winning team probabilities as well as their predictions. If, however, making detailed predictions make people more likely to believe that the upcoming games would somehow be unique and that “this time will be different”, their winning team probabilities should be unchanged.

In Experiments 7, 9, 11, and 14-15, participants gave their win probabilities by entering how many times out of 100 the home team would win. In Experiments 16-19 they gave their probabilities by entering how many times out of 100 both teams would win (and the numbers were required to sum to 100).

Figure A2 1. Winning team probability instructions.

In this portion of the survey, you will see the same [X] [sports league] games scheduled to be played from today, Thursday January 29th through Sunday February 1st.

For each game, we will ask you to **imagine that the two teams played that exact game 100 times**.

What we mean by "that exact game" is that each of the 100 times the game is played, the game would begin with the <u>exact same starting conditions as the actual game</u>.

For example, the location of the game, the home team, the win/loss records of each team, the player lineup, player injuries, etc. <u>would all be the same at the beginning of each of the 100 games as they are at the beginning of the actual game</u>.

For each game, we will ask you to tell us how many times you think [the home team / each team] would win if they played that exact game 100 times.

Note. “X” is the number of games they made predictions for in the experiment and “sports league” is the sport league of the games (e.g., Major League Baseball).

Then, on the next few pages, participants revisited each game and reported how may times out of 100 they thought each team would win if they were to play that exact game 100 times.

Figure A2 2. Winning team probability question format (Experiments 7, 9, 11, and 14-15).

Imagine these two teams played this exact game 100 times.

How many games (out of 100) do you think the **[home team]** would win? [ ]

Figure A2 3. Winning team probability question format (Experiments 16-19).

Imagine these two teams played this exact game 100 times.

[0] How many games (out of 100) would the **[visiting team]** win?

[0] How many games (out of 100) would the **[home team]** win?

Quality of winning team probabilities. Each winning team probability can be coded as either agreeing with the wise prediction (i.e., they said the market favorite would win more than 50 out of 100 games) or disagreeing with the wise prediction. Then we can compare the average percentage of winning team probabilities that agreed with the market favorites across prediction conditions to see if making detailed predictions changed people's beliefs about whether the market favorite was likely to win.

Table A2 1. Average % of winning team probabilities that agreed with the market favorite.

Winner	Score + Winner	Relevant + Winner	Irrelevant + Winner
72.2% (.108)	71.8% (.113)	71.5% (.114)	71.8% (.124)

Note. All means in the table are mean-centered with experiment as the grouping factor. Within each row, means with different subscripts differ at p < .05 using within-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979).

Consistency of winning team probabilities with predictions. Each winning team probability can be coded as either consistent with the participants' own predictions (i.e., they said that the team they predicted to win the actual game would more than 50 out of 100 games) or inconsistent. Then we can compare the average percentage of consistent predictions across prediction conditions to see if making detailed predictions made people more likely to deviate from their own beliefs about which teams were more likely to win.

Table A2 2. Average % of winning team probabilities that were consistent with the participants' own predictions.

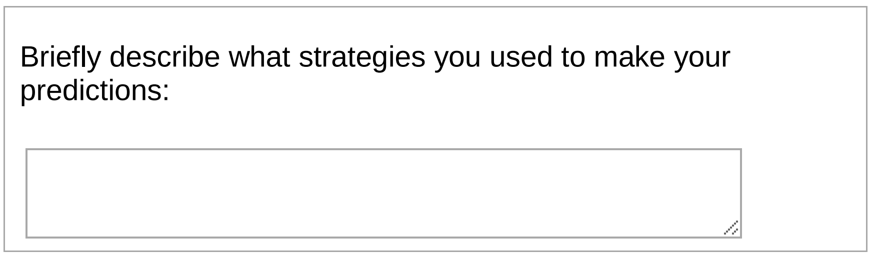
Winner	Score + Winner	Relevant + Winner	Irrelevant + Winner
82.3%$_{a}$ (.162)	79.9%$_{b}$ (.113)	79.5%$_{b}$ (.114)	80.9%$_{ab}$ (.124)

Note. All means in the table are mean-centered with experiment as the grouping factor. Within each row, means with different subscripts differ at p < .05 using within-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979).

Prediction strategy (Experiments 3-6, 8, 10, 12)

On a separate page, immediately after making their predictions for each game, participants described the strategies they used to make their predictions in an open-ended format. Participants were required to enter a minimum of 25 characters to proceed to the next page of the survey.

Figure A2 4. Prediction strategy question format.



In early studies, responses were read by the authors for exploratory purposes. None of the prediction strategy responses for any experiments have been formally coded or analyzed because we did not believe that participants would be aware of how the manipulations affected their thought processes (Nisbett & Wilson, 1977).

"Global" and "local" considerations (Experiments 1-16, E1-E8)

On a separate page, participants rated how much they considered each of several factors when making their predictions on a scale from 1 to 7 (see labels below). The display order of these items was randomized between subjects.

We used the exact "global" considerations (items 1-3 below, α = .68) and "local" considerations (items 4-6 below, α = .85) from Yoon et al. (2013). Yoon and colleagues describe “global” information as “comprehensive data that indicate the overall circumstances of the issue (e.g., past performance of two teams)”, and “local” information as information that “although more specific and detailed, reveals only partial information and is therefore less informative about the overall picture of the event (e.g., the offense ability of two teams)” (p. 5). For experiments that used baseball predictions, we added a fourth “local” consideration specific to baseball (item 7) that did not appear in Yoon et al. (2013).

Figure A2 5. "Global" and "local" considerations question format.

Please indicate the degree to which you considered each of these factors while making your predictions:

	not considered at all						seriously considered
overall impression of the two teams	O	O	O	O	O	O	O
overall performance of the two teams in the past years	O	O	O	O	O	O	O
overall performance of the two teams in recent years	O	O	O	O	O	O	O
the teams’ offensive abilities	O	O	O	O	O	O	O
the teams’ defensive abilities	O	O	O	O	O	O	O
the teams’ coaching abilities	O	O	O	O	O	O	O
the teams’ pitching abilities [baseball only]	O	O	O	O	O	O	O

Table A2 3. Means and standard deviations of "global" and "local" considerations.

	Winner	Score†	Relevant + Winner	Irrelevant + Winner
overall impression of the two teams	5.45_{a} (1.47)	5.55_{b} (1.40)	5.54_{ab} (1.45)	5.51_{ab} (1.43)
overall performance of the two teams in the past years	4.53 (1.84)	4.46 (1.83)	4.44 (1.86)	4.49 (1.79)
overall performance of the two teams in recent years	4.89 (1.77)	4.84 (1.74)	4.84 (1.77)	4.83 (1.69)
Global considerations	4.95 (1.34)	4.95 (1.30)	4.94 (1.31)	4.94 (1.27)
the teams' offensive abilities	4.47_{a} (1.82)	4.70_{b} (1.78)	4.70_{b} (1.76)	4.60_{ab} (1.72)
the teams' defensive abilities	3.98 (1.79)	4.06 (1.77)	4.11 (1.75)	4.13 (1.70)
the teams' coaching abilities	3.41 (1.76)	3.35 (1.74)	3.35 (1.72)	3.49 (1.75)
the teams' pitching abilities [baseball only]	4.85 (1.96)	4.85 (1.89)	4.87 (1.96)	5.15 (1.88)
Local considerations	4.11 (1.57)	4.18 (1.51)	4.20 (1.49)	4.22 (1.53)

Note. †Score includes all conditions where participants predicted the final score. All means in the table are mean-centered with experiment as the grouping factor. Within each row, means with different subscripts are significantly different at $p < .05$ with pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons.

Table A2 4. Correlations of "global" and "local" considerations with winning team prediction quality.

	Winner	Score†	Relevant + Winner	Irrelevant + Winner
overall impression of the two teams	.06***	.12***	.03	.10*
overall performance of the two teams in the past years	-.04*	.00	-.11***	-.11*
overall performance of the two teams in recent years	.01	.04*	-.04	.01
Global considerations	.01	.06***	-.06*	-.01
the teams' offensive abilities	.05**	.11***	.04	.09*
the teams' defensive abilities	-.01	.00	-.08**	.04
the teams' coaching abilities	-.07***	-.06***	-.11***	-.01
the teams' pitching abilities [baseball only]	.16***	.13***	.12***	.07
Local considerations	.02	.05**	-.02	.05

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. †Score includes all conditions where participants predicted the final score.

"This time" vs. "usually" considerations (Experiments 17-19)

In the last three experiments, instead of asking about "local" and "global" factors, we asked participants several questions designed to identify whether they were thinking of the upcoming games as unique or distinct from games in the past. They rated how much they thought about past performance (items 1, 3, and 5) and how much they thought about expected future performance (items 2, 4, and 6) on a scale from 1 to 7 (see labels below).

Figure A2 6. "This time" and "usually" considerations question format.

Please indicate the degree to which you considered each of these factors while making your predictions:

	not considered at all						seriously considered
The overall performance of the two teams so far this season	O	O	O	O	O	O	O
Whether I expected either team to perform better or worse that game than they usually do	O	O	O	O	O	O	O
The typical quality of the teams' offenses	O	O	O	O	O	O	O
How the teams' offensive lineups will look that game	O	O	O	O	O	O	O
The typical quality of the teams' defenses	O	O	O	O	O	O	O
How the teams' defensive lineups will look that game.	O	O	O	O	O	O	O

Table A2 5. Means and standard deviations of "this time" and "usually" considerations.

	Winner	Score + Winner	Irrelevant + Winner
The overall performance of the two teams so far this season	6.15 (1.07)	6.02 (1.20)	6.15 (1.07)
Whether I expected either team to perform better or worse that game than they usually do	4.58 (1.58)	4.60 (1.61)	4.58 (1.58)
The typical quality of the teams' offenses	4.61 (1.62)	4.75 (1.63)	4.61 (1.62)
How the teams' offensive lineups will look that game	3.98 (1.75)	4.08 (1.75)	3.98 (1.75)
The typical quality of the teams' defenses	4.42 (1.65)	4.61 (1.65)	4.42 (1.65)
How the teams' defensive lineups will look that game.	3.92 (1.74)	4.03 (1.73)	3.92 (1.74)

Note. All means in the table are mean-centered with experiment as the grouping factor. Within each row, means with different subscripts are significantly different at $p < .05$ with pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons.

Table A2 6. Correlations of "this time" and "usually" considerations with winning team prediction quality.

	Winner	Score + Winner	Irrelevant + Winner
The overall performance of the two teams so far this season	.13***	.23***	.31***
Whether I expected either team to perform better or worse that game than they usually do	-.11**	-.11**	-.12***
The typical quality of the teams' offenses	-.07.	-.03	-.05
How the teams' offensive lineups will look that game	-.13***	-.11**	-.11**
The typical quality of the teams' defenses	-.09*	-.10*	-.10**
How the teams' defensive lineups will look that game.	-.14***	-.13***	-.15***

* $p < .05$, ** $p < .01$, *** $p < .001$. [†]Score includes all conditions where participants predicted the score.

Confidence and motivation (Experiments 3-19, E1-E8)

On a separate page, participants rated both how confident they were in their predictions and how motivated they were to make accurate predictions on scales from 1 to 7 (see labels below). They made these ratings for each type of prediction they made; for example, participants in the Score + Winner condition would rate their confidence and motivation for both their final score predictions and their winning team predictions. For each type of prediction, the motivation question was always immediately followed the confidence question. For participants who made detailed predictions, they rated the motivation and confidence for the detailed predictions before the winning team predictions (i.e., the same order that they made the predictions in the survey). All confidence and motivation questions for all predictions were displayed on a single page.

Figure A2 7. Confidence and motivation question format.

Overall, how confident were you in the [outcome] predictions that you made?

not at all confident						extremely confident
O	O	O	O	O	O	O

Overall, how motivated were you to correctly predict the [outcome] for each game?

not at all motivated						extremely motivated
O	O	O	O	O	O	O

Note. For confidence questions, [outcome] was replaced with the appropriate prediction type for the participant's condition assignment: {"final score", "hits", "total runs", "game time", "total points", "predictions you made about the % of U.S. citizens in the crowd", "free throw", "temperature", "winning team"}. For the motivation questions, [outcome] was replaced with the appropriate prediction type for the participant's condition assignment: {"final score", "number of hits each team will get", "total number of runs scored", "total game time", "total points scored", "% of U.S. citizens in the crowd", "number of free throws each team will attempt", "temperature outside the arena at the start of each game", "winning team"}.

Table A2 7. Means and standard deviations of confidence and motivation.

	Winner	Score†	Relevant + Winner	Irrelevant + Winner
confidence in winner prediction	4.83 (1.15)	4.82 (1.33)	4.90 (1.24)	4.79 (1.19)
confidence in detailed prediction	-	3.84_a (1.50)	3.67_b (1.52)	3.81_a (1.53)
motivation to correctly predict winner	6.11_a (1.07)	6.01_b (1.16)	6.09_{ab} (1.15)	6.03_{ab} (1.04)
motivation to correctly predict detail	-	5.16_a (1.63)	4.91_b (1.76)	4.87_b (1.73)

Note. †Score includes all conditions where participants predicted the final score. All means in the table are mean-centered with experiment as the grouping factor. Within each row, means with different subscripts are significantly different at $p < .05$ with pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons.

Table A2 8. Correlations of confidence and motivation with winning team prediction quality.

	Winner	Score†	Relevant + Winner	Irrelevant + Winner
confidence in winner prediction	.11***	.15***	.09***	.16***
confidence in detailed prediction	-	-.01	-.03	-.04
motivation to correctly predict winner	.15***	.20***	.19***	.20***
motivation to correctly predict detail	-	.05**	.02	-.05

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. †Score includes all conditions where participants predicted the final score.

Thinking carefully and effortfully (Experiments 13, 14, 19)

These questions were included in three experiments where we manipulated the incentives for correct predictions within-subjects for different games. The ordering and format of these questions differed between Experiments 13-14 and Experiment 19.

In Experiments 13 and 14, we first informed participants that they would be rewarded a 5-cent bonus each time they correctly predicted the winning team. After making sixteen predictions, they reported “Overall, how carefully did you think about each game before making your winning team predictions?” and “Overall, how much effort did you invest in thinking about and making your predictions?” We then informed them that the amount of the bonus had been increased to 25 cents per correct winning team prediction for a remaining block of games. They then made predictions about an additional sixteen games and rated how carefully they thought about and how much effort they invested in making predictions for just those sixteen 25-cent games.

In Experiment 19, we informed participants at the beginning of the survey that some games would be worth more than others. They then made all thirty low- and high-incentive predictions at once. The amount of the bonus (5 cents vs. 20 cents) was displayed prominently and alternated between games. After making all of their predictions, they rated how carefully they thought about and how much effort they invested in making their predictions separately for the 5-cent games and the 20-cent games.

Figure A2 8. Thinking carefully and effortfully question format.

Overall, how carefully did you think about [each game / each of the 5 cent games / each of the 20 cent games] before making your winning team predictions?

not at all carefully						extremely carefully
O	O	O	O	O	O	O

Overall, how much effort did you invest in thinking about and making your predictions [for the 5 cent games / for the 20 cent games]?

no effort at all						extreme amounts of effort
O	O	O	O	O	O	O

Table A2 9. Means and standard deviations of careful and effortful thinking.

	Winner	Score + Winner
careful (small incentive games)	5.47 (1.30)	5.45 (1.29)
careful (large incentive games)	5.84 (1.20)	5.83 (1.19)
effort (small incentive games)	5.41 (1.32)	5.53 (1.25)
effort (large incentive games)	5.78 (1.20)	5.86 (1.17)

Note. All means in the table are mean-centered with experiment as the grouping factor. Within each row, means with different subscripts are significantly different at $p < .05$ with pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons.

Table A2 10. Correlations of careful and effortful thinking with winning team prediction quality.

	Winner	Score + Winner
careful (small incentive games)	.04	.14***
careful (large incentive games)	.06	.14***
effort (small incentive games)	.01	.11**
effort (large incentive games)	.02	.16***

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

Outcome variability (Experiments 8, 10)

On a separate page, participants were first asked to imagine that two teams played two games with the exact same starting conditions (players, location, weather, etc.). Then they were asked to rate how likely each type of outcome was to be different in the second game than in the first game on scales from 1 to 7 (see labels below). They made these ratings for each type of outcome they made predictions about; for example, participants in the Hits + Winner condition first rated how likely the exact number of hits scored by each team was to be different in the second game than in the first game, and then they rated how likely the winning team was to be different in the second game than in the first game.

Figure A2 9. Outcome variability instructions.

In the following questions, we will ask you to **imagine that two teams play each other twice, and that both games have the exact same starting conditions**. This means that the teams, the stadium, team records, player lineups, starting pitchers, player injuries, streaks, etc. would all be exactly the same at the start of both games.

Figure A2 10. Outcome variability question format.

If two teams played each other in two games with the exact same starting conditions, how likely is it that the [outcome] of the first game would be different from the [outcome] of the second game?

it would definitely not be different	very unlikely to be different	somewhat unlikely to be different	somewhat likely to be different	very likely to be different	it would definitely be different
O	O	O	O	O	O

Note. [Outcome] was replaced with the appropriate game outcome for the participant's condition: {"exact final score", "exact number of hits per team", "combined total number of runs scored", "winning team"}.

Table A2 11. Means and standard deviations of outcome variability.

	Winner	Score + Winner	Hits + Winner	Runs + Winner
winner prediction variability	3.49 (0.903)	3.47 (0.810)	3.58 (0.845)	3.62 (0.849)
detailed prediction variability	-	4.43 (1.029)	4.46 (0.986)	4.54 (0.891)

Note. All means in the table are mean-centered with experiment as the grouping factor. Within each row, means with different subscripts are significantly different at $p < .05$ with Holm-Bonferroni-corrected pairwise t-tests.

Table A2 12. Correlations of outcome variability with winning team prediction quality.

	Winner	Score + Winner	Hits + Winner	Runs + Winner
winner prediction variability	.01	-.10	-.02	.01
detailed prediction variability	-	.14*	.11*	.15**

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

Outcome usefulness for predicting the winning team (Experiments 8, 10)

On the same page as the outcome variability questions, and after those questions, participants were asked how useful the detailed outcome they made predictions about was for predicting which team won the game on a scale from 1 to 5 (see labels below). Participants in conditions that only made winning team predictions were not asked this question.

Figure A2 11. Outcome usefulness for predicting the winning team question format.

Imagine you knew the [outcome] in a MLB baseball game. How much would this help you predict who won that game?

completely useless for predicting the winner	slightly useful for predicting the winner	moderately useful for predicting the winner	extremely useful for predicting the winner	I could tell with certainty who won the game
O	O	O	O	O

Note. [Outcome] was replaced with one of the following, depending on condition: {“exact number of runs that each team scored (i.e. the final score)”, “exact number of hits that each team got”, “combined total number of runs scored during the game”}. Rationally, the exact final score should always be rated 5, the combined total number of runs scored during the game should always be rated 1, and the exact number of hits each team got should be rated somewhere in-between.

Table A2 13. Means and standard deviations of outcome usefulness for predicting the winning team.

Exact final score	Exact number of hits	Total number of runs
3.74_a (1.03)	3.40_b (0.79)	2.74_c (1.05)

Note. All means in the table are mean-centered with experiment as the grouping factor. Within each row, means with different subscripts are significantly different at p < .05 with Holm-Bonferroni-corrected pairwise t-tests.

Table A2 14. Correlations of outcome usefulness for predicting the winning team with winning team predictions quality.

Exact final score	Exact number of hits	Total number of runs
.01	.02	-.08

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

Team liking (Experiment 12)

On a separate page, participants rated how much they disliked or liked each of the 32 teams that played in the 2014 FIFA World Cup on a 7-point scale from -3 to +3 (see labels below). Teams were listed in alphabetical order and the scale labels repeated every 7 teams.

Figure A2 12. Team liking question format.

In general, how much do you like or dislike each team?

	I hate this team	I very much dislike this team	I somewhat dislike this team	I neither like nor dislike this team	I somewhat like this team	I very much like this team	I love this team
Algeria	O	O	O	O	O	O	O
Argentina	O	O	O	O	O	O	O
Australia	O	O	O	O	O	O	O
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Uruguay	O	O	O	O	O	O	O

Note. Participants gave liking ratings for all 32 teams in the 2014 FIFA World Cup: Algeria, Argentina, Australia, Belgium, Bosnia and Herzegovina, Brazil, Cameroon, Chile, Colombia, Costa Rica, Côte d'Ivoire, Croatia, Ecuador, England, France, Germany, Ghana, Greece, Honduras, Iran, Italy, Japan, Korea Republic, Mexico, Netherlands, Nigeria, Portugal, Russia, Spain, Switzerland, United States, Uruguay.

Table A2 15. Means and standard deviations of liking ratings by country.

United States	England	Brazil	Spain
1.91 (1.27)	0.85 (1.23)	0.85 (1.31)	0.58 (1.14)
Germany	**Argentina**	**Italy**	**Netherlands**
0.55 (1.27)	0.49 (0.99)	0.46 (1.15)	0.41 (0.92)
Australia	**Portugal**	**Switzerland**	**Japan**
0.37 (0.88)	0.33 (0.99)	0.30 (0.79)	0.30 (1.03)
Belgium	**Chile**	**France**	**Colombia**
0.28 (0.80)	0.23 (0.85)	0.22 (1.17)	0.18 (0.86)
Uruguay	**Mexico**	**Costa Rica**	**Ecuador**
0.18 (0.80)	0.17 (1.26)	0.16 (0.81)	0.12 (0.79)
Greece	**Korea Republic**	**Honduras**	**Cameroon**
0.06 (0.83)	0.06 (0.97)	0.04 (0.75)	0.04 (0.79)
Côte d'Ivoire	**Croatia**	**Nigeria**	**Bosnia-Herzegovina**
0.03 (0.84)	0.03 (0.77)	0.01 (0.77)	-0.04 (0.73)
Algeria	**Ghana**	**Russia**	**Iran**
-0.10 (0.66)	-0.12 (1.04)	-0.20 (1.07)	-0.50 (1.05)

Note. Countries are listed in descending order by average liking rating.

The liking ratings for the different countries' teams did not differ significantly between conditions, so instead we present the average liking ratings by country in descending order.

Effect of team liking on winning team predictions.

How much more participants liked one team versus the other was significantly positively correlated with predicting that team to win the game, $r(29182) = 0.26$, $p < .001$. However, there was no interaction between how much more participants liked the superior team than the inferior team and whether or not they predicted the score on winning team prediction quality.

Predicted the superior team to win values: {0, 1}	=	Difference in liking (superior minus inferior team) values: [-6, +6]	X	Predicted the score (Score+Winner condition) values: {0, 1}

Table A2 16. Effect of liking on winning team prediction quality.

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.607	0.004	157.36	< 0.001	***
liking difference	0.096	0.003	32.79	< 0.001	***
predicted score	-0.032	0.006	-5.70	< 0.001	***
liking difference x predicted score	-0.005	0.004	-1.31	0.19	

Note. *p < .05, **p < .01, ***p < .001.

Self-reported sports following and knowledge (Experiments 6-19, E5-E8)

On a separate page, participants rated how closely they followed the sport league used in the experiment (e.g., Major League Baseball) and how knowledgeable they were about that sport league on scales from 1 to 7 (see labels below).

Figure A2 13. Self-reported sports following and knowledge question format.

How closely do you follow [sport league]?

not at all						extremely closely
O	O	O	O	O	O	O

How knowledgeable are you about [sport league]?

not at all knowledgeable						extremely knowledgeable
O	O	O	O	O	O	O

Note. [Sport league] was replaced with the relevant sport for the experiment: {"MLB baseball", "NFL football", "NHL hockey", "NBA basketball", "FIFA soccer"}

Figure A2 14. Histograms of responses for self-reported sports knowledge and following.

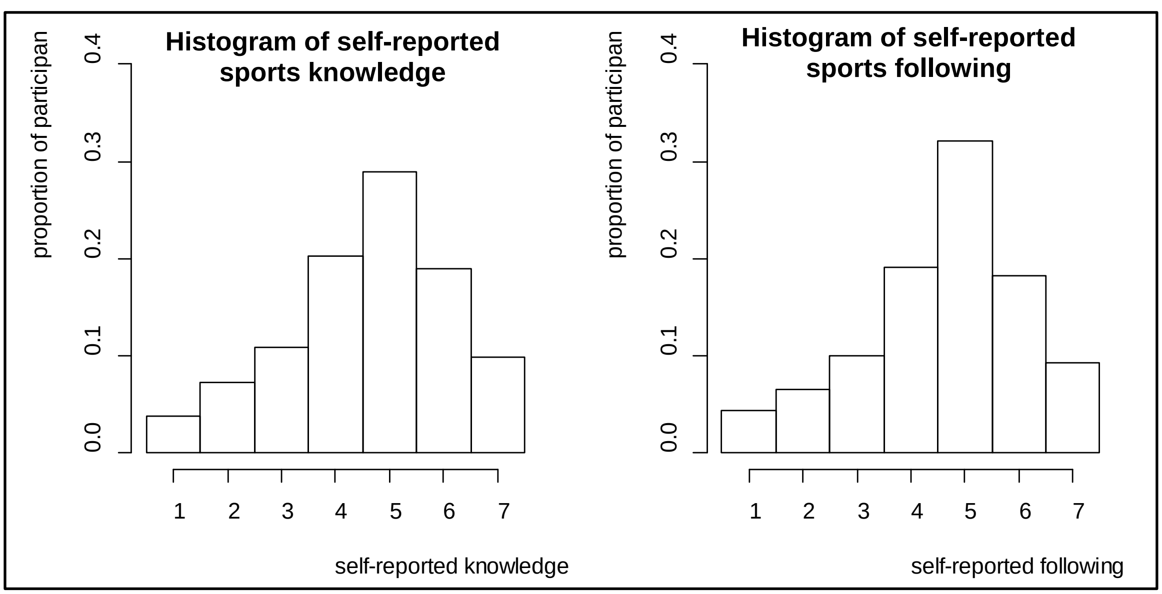


Table A2 17. Means and standard deviations of self-reported sports knowledge and following.

	Winner	Score + Winner	Relevant + Winner	Irrelevant + Winner
self-reported sports knowledge	4.62 (1.47)	4.60 (1.45)	4.60 (1.53)	4.56 (1.45)
self-reported sports following	4.62 (1.48)	4.58 (1.45)	4.60 (1.53)	4.56 (1.45)

Note. All means in the table are mean-centered with experiment as the grouping factor. Within each row, means with different subscripts are significantly different at $p < .05$ with pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons.

Table A2 18. Correlations of self-reported sports knowledge and following with winning team prediction quality.

	Winner	Score + Winner	Relevant + Winner	Irrelevant + Winner
self-reported sports knowledge	.15***	.17***	.13***	.11***
self-reported sports following	.15***	.16***	.15***	.13***

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

Measured knowledge (Experiments 1-19, E1-E8)

On a separate page, participants answered 8 questions designed to assess their knowledge of the sport league used in the study. The display order of these questions was randomized between participants. The questions used varied between experiments. Participants were encouraged to leave the questions blank if they didn't know the answer rather than guessing the answer.

Two of the eight questions were about which division a given sports team belonged to. For each of these questions, participants were prompted to select the division that a given team belonged to from a drop-down list containing all divisions in the sports league. Major League Baseball has two major leagues with three divisions each for a total of six divisions, the National Football League has two major conferences with four divisions each for a total of eight divisions, the National Hockey League has two major conferences with two divisions each for a total of four divisions, and the National Basketball Association has two major conferences with three divisions each for a total of six divisions. The two sports teams were chosen so that there was one from each of the two major leagues/conferences. The teams used in these questions varied between experiments.

Six of the eight questions asked about which teams relatively well-known players played for. For each of these questions, participants were prompted to select the team that a given player played for from a drop-down list containing all teams in the sports league. For baseball and basketball, players were chosen so that there was one player from each of the six different divisions in the league. For hockey, players were chosen so that there was at least one player from each of the four different divisions, and the remaining two players were drawn from teams from different conferences. For football, players were chosen so that each player was from a different division and there were three players from each conference. The players used in these questions varied between experiments.

For the 2014 FIFA World Cup (Experiment 12), all eight questions were about which teams various players belonged to, and players were chosen at random from a list of the top 25 well-known players in FIFA that were participating in the World Cup in 2014.

Figure A2 15. Measured sports knowledge instructions.

In this section, we will ask you 8 questions designed to assess your [sports league] knowledge. Please answer each of the following questions to the best of your ability.

Please do NOT look up the answers while completing this section. It is important for us to have an accurate sense of your baseball knowledge. **Your bonus payment will <u>not</u> be affected by how you answer these questions.**

If you do not know an answer, please leave it blank and move on to the next question.

Figure A2 16. Example of measured knowledge question format (team/division matching).

In which division do the [sports team] play?

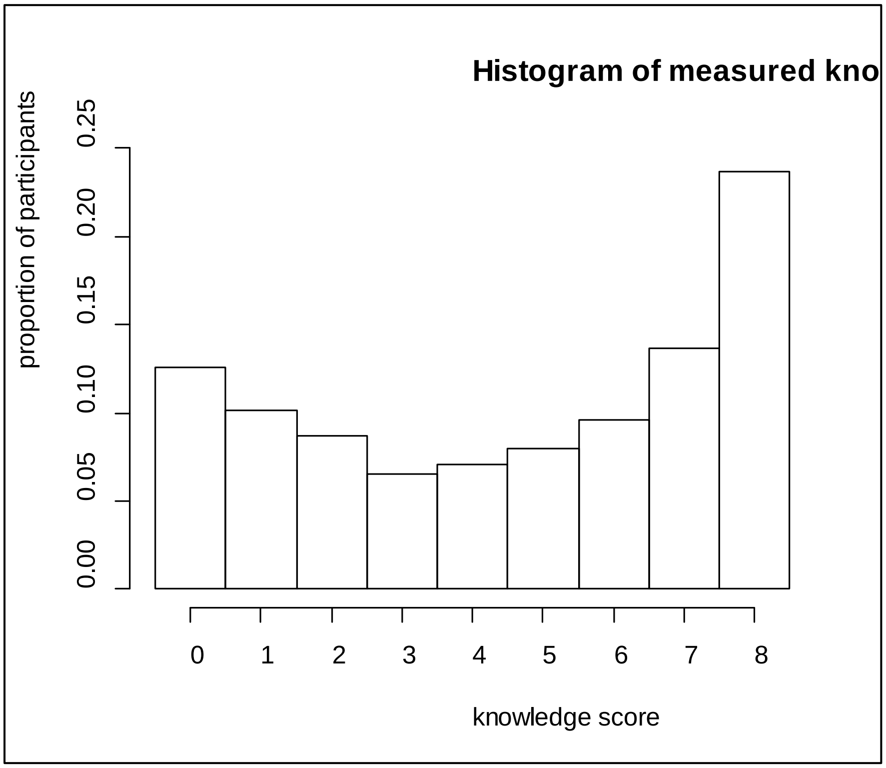
American League East
American League Central
American League West
National League East
National League Central
National League West

Figure A2 17. Example of measured knowledge question format (player/team matching).

Which MLB team does [player] play for?

Arizona Diamondbacks
Atlanta Braves
Baltimore Orioles
Boston Red Sox

Figure A2 18. Histogram of measured knowledge scores.



Unlike most self-reported measures, knowledge scores did not follow a normal distribution. Rather, most participants scored either on the low end or the high end of the range, and relatively few people in the middle of the range.

Table A2 19. Means and standard deviations of measured knowledge scores.

Winner	Score†	Relevant + Winner	Irrelevant + Winner
4.62 (2.86)	4.56 (2.85)	4.61 (2.96)	4.53 (2.73)

Note. †Score includes all conditions where participants predicted the final score. All means in the table are mean-centered with experiment as the grouping factor. Within each row, means with different subscripts are significantly different at $p < .05$ with pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons.

Table A2 20. Correlations of measured sports knowledge with winning team prediction quality.

Winner	Score†	Relevant + Winner	Irrelevant + Winner
.23***	.23***	.20***	.23***

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. †Score includes all conditions where participants predicted the final score.

Maximizing Tendency Scale (Experiments 1-2)

This scale was included at the end of Experiments 1 and 2 on a separate page after all other measures other than age, gender, and optional contact information. These questions were included as a pilot for a separate research question, and so we will not discuss them further.

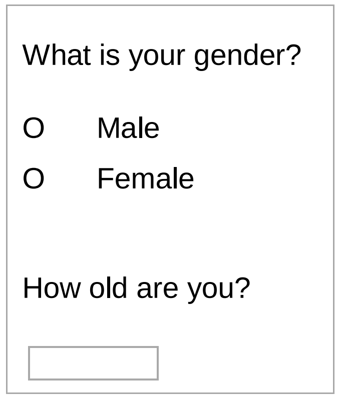
Figure A2 19. Maximizing Tendency Scale question format.

	completely disagree			neither agree nor disagree			completely agree
No matter what it takes, I always try to choose the best thing.	O	O	O	O	O	O	O
I don't like having to settle for "good enough".	O	O	O	O	O	O	O
I am a maximizer.	O	O	O	O	O	O	O
No matter what I do, I have the highest standards for myself.	O	O	O	O	O	O	O
I will wait for the best option no matter how long it takes.	O	O	O	O	O	O	O
I never settle for second best.	O	O	O	O	O	O	O
I am uncomfortable making decisions before I know all of my options. [Reverse-coded]	O	O	O	O	O	O	O
Whenever I'm faced with a choice, I try to imagine what all the other possibilities are, even ones that aren't present at the moment.	O	O	O	O	O	O	O
I never settle.	O	O	O	O	O	O	O
	completely disagree			neither agree nor disagree			completely agree

Gender and age (Experiments 1-19, E1-E8)

On a separate page, participants reported their gender and age.

Figure A2 20. Gender and age question format.


What is your gender?

O Male

O Female

How old are you?

Averages and correlations. Across all experiments, most participants were male (73.2%) and an average of 30.9 years old (SD = 9.9). Being female was significantly negatively correlated with making wise predictions, r(10,323) = -.07, p < .001, and age was uncorrelated with wise predictions.

Instruction difficulty/confusion (Experiments 7, 9, 11, 14-19)

On same page as gender and age, after these questions, participants reported how difficult the survey was to understand (Experiment 7) or how confusing the instructions were (Experiments 9, 11, 14-19) on scales from 1 to 4 (see labels below). We included this question in all experiments where participants reported winning team probabilities because we were worried that some participants would be confused by the instructions to imagine two teams playing the exact same game 100.

Figure A2 21. Question difficulty question format (Experiment 7).

How difficult was this survey to understand?

not at all difficult	slightly difficult	moderately difficult	extremely difficult
O	O	O	O

Figure A2 22. Question difficulty question format (Experiments 9, 11, and 14-19).

How confusing were the instructions in this survey?

not at all confusing	slightly confusing	moderately confusing	extremely confusing
O	O	O	O

Table A2 21. Summary of responses to question difficulty.

	not at all [difficult/confusing]	slightly [difficult/confusing]	moderately [difficult/confusing]	extremely [difficult/confusing]
N	4009	952	330	52
%	87.0%	10.3%	2.4%	0.3%

Across experiments, the vast majority of participants rated the survey to be “not at all [difficult/confusing]”.

Contact for future studies (Experiments 1-19, E1-E8)

On the same page as gender and age, after all other questions, participants were asked whether they would like to be contacted to participate in future sports studies, and if so, to give a contact e-mail address. We did not use the information collected in this section to recruit for any experiments.

Figure A2 23. Contact for future studies sport selection.

Would you like to participate in future studies that allow you to win money by making predictions about sports? If so, check the boxes for the sports you are interested in and enter your email address in the box below:

- □ Major League Baseball
- □ National Basketball Association
- □ National Football League
- □ National Hockey League
- □ Fédération Internationale de Football Association (FIFA) [Experiment 12 only]

Note. The checklist for different sports leagues was only used in Experiments 6-19 and E4-E8. For Experiments 1-5 and E1-E3, participants were asked "Would you like to participate in future studies that allow you to win money by making predictions about [Major League Baseball / the National Football League]? If so, please enter your email address in the box below." This statement was then followed by the email entry box and privacy disclaimer displayed below.

Figure A2 24. Contact for future studies e-mail entry.

(If you enter your email address then University of Pennsylvania researchers may occasionally email you links to surveys about the sports you selected. We will NEVER share your email address with anyone).

APPENDIX A3. ALTERNATIVE ANALYSES

In this document, we report several alternative analyses for each of the main findings reported in the Results section of the main text.

Definition of Prediction Quality

Our research investigates how making detailed predictions about sports affects prediction quality. In the main text, we defined *wise* predictions as choosing the team favored by betting markets. However, there are several possible ways to define a wise prediction:

- **Odds**: Choosing the team favored by well-calibrated betting markets (the definition used in the main text).
- **Records**: Choosing the team that had won a greater percentage of past games.
- **Accuracy**: Choosing the team that actually won the game.

In the main text we explain why the best definition for a wise prediction is choosing the team favored by well-calibrated betting markets ("Odds"), but in this Appendix we reproduce the main results for all three definitions.

Level of Analysis

We also chose to analyze wise predictions in the main text at the game level, examining for each game whether a greater percentage of participants made wise predictions when they were simply asked to select the winning team than when they were also (or instead) asked to make a detailed prediction. However, there are multiple ways we could have analyzed wise predictions:

- **Game-Level Analysis**: Treat each game as an observation and compare the percentage of participants making wise predictions between different conditions as within-subjects measures (the method used in the main text).
- **Participant-Level Analysis**: Treat each participant as an observation and compare the average percentage of wise predictions made by participants in different conditions.
- **Prediction-Level Analysis**: Treat each prediction as an observation and compare the percentage of wise predictions between conditions.

In the main text, we explain that using game as the level of analysis has the benefit of controlling for differences across games, while also allowing us to explore whether effects emerge for some games and not others. However, the other methods outlined above are reported in this Appendix.

Summary of experimental results

The tables in this section report alternative analyses for the data presented in Table 1 in the main text displaying the percentage of wise predictions made in each condition in each experiment.

Table A3 1. Game-Level Analyses. Experiments 1-19: The average percentage of participants making wise predictions in each prediction condition for each experiment.

Exper-iment	Sport League	# of subjects	# of games	Wise Prediction	Winner Only	Score Only	Score +Winner	Relevant +Winner	Irrelevant +Winner
				Odds	$67.3\%_a$	$61.4\%_b$	-	-	-
1	MLB	316	41	Records	$69.5\%_a$	$65.1\%_b$	-	-	-
				Accuracy	53.5%	52.4%	-	-	-
				Odds	$73.3\%_a$	$67.4\%_c$	$69.7\%_b$	-	-
2	MLB	508	39	Records	$78.8\%_a$	$72.5\%_c$	$75.0\%_b$	-	-
				Accuracy	$42.2\%_b$	$46.4\%_a$	$44.2\%_{ab}$	-	-
				Odds	$63.4\%_a$	$57.5\%_c$	$60.2\%_b$	-	-
3	MLB	635	45	Records	$71.5\%_a$	$65.2\%_c$	$71.7\%_b$	-	-
				Accuracy	52.7%	51.5%	51.2%	-	-
				Odds	$70.8\%_a$	-	$66.6\%_b$	$66.8\%_b$	-
4	MLB	631	45	Records	$76.9\%_a$	-	$72.2\%_c$	$74.0\%_b$	-
				Accuracy	51.9%	-	49.8%	50.0%	-
				Odds	60.1%	-	58.8%	58.8%	60.2%
5	MLB	634	42	Records	$78.9\%_{ab}$	-	$76.8\%_b$	$79.2\%_a$	$78.9\%_{ab}$
				Accuracy	49.2%	-	48.5%	48.8%	48.3%
				Odds	$53.5\%_a$	-	$49.8\%_b$	-	-
6	NHL	309	29	Records	$58.4\%_a$	-	$55.4\%_b$	-	-
				Accuracy	56.8%	-	54.4%	-	-
				Odds	$56.6\%_a$	-	$53.9\%_b$	-	-
7	MLB	337	45	Records	$73.1\%_a$	-	$70.4\%_b$	-	-
				Accuracy	47.2%	-	47.2%	-	-
				Odds	56.7%	-	55.7%	55.8%	-
8	MLB	625	44	Records	$73.6\%_a$	-	$71.2\%_b$	$71.4\%_b$	-
				Accuracy	51.8%	-	51.6%	51.1%	-
				Odds	60.9%	-	59.7%	-	-
9	MLB	422	41	Records	73.4%	-	74.0%	-	-
				Accuracy	$44.4\%_b$	-	$45.9\%_a$	-	-
				Odds	59.3%	-	58.4%	58.5%	-
10	MLB	728	45	Records	$77.4\%_a$	-	$75.2\%_b$	$76.3\%_{ab}$	-
				Accuracy	54.4%	-	54.7%	54.7%	-
				Odds	$63.4\%_a$	-	$61.8\%_b$	-	-
11	MLB	525	42	Records	71.6%	-	70.5%	-	-
				Accuracy	46.6%	-	46.8%	-	-

(table continued on next page)

Exper-iment	Sport League	# of subjects	# of games	Prediction Quality	Winner Only	Score Only	Score +Winner	Relevant +Winner	Irrelevant +Winner
12	FIFA	622	48	Odds	$61.2\%_a$	-	$57.8\%_b$	-	-
				Records	-	-	-	-	-
				Accuracy	49.7%	-	48.4%	-	-
13	NBA	420	32	Odds	70.3%	-	70.9%	-	-
				Records	$79.1\%_a$	-	$77.8\%_b$	-	-
				Accuracy	62.1%	-	61.7%	-	-
14	NHL	541	32	Odds	70.0%	-	70.8%	-	-
				Records	82.0%	-	81.4%	-	-
				Accuracy	55.4%	-	55.9%	-	-
15	NBA	775	32	Odds	74.1%	-	72.9%	72.4%	72.6%
				Records	$86.2\%_a$	-	$84.6\%_b$	$83.7\%_b$	$83.4\%_b$
				Accuracy	60.2%	-	60.7%	60.2%	59.4%
16	NHL	711	30	Odds	73.3%	-	72.4%	71.4%	73.0%
				Records	$81.6\%_{ab}$	-	$80.6\%_{bc}$	$78.0\%_d$	$79.3\%_{cd}$
				Accuracy	55.2%	-	54.6%	54.4%	55.9%
17	NHL	811	31	Odds	$74.8\%_a$	-	$70.8\%_b$	-	$75.2\%_a$
				Records	$83.6\%_a$	-	$80.3\%_b$	-	$83.4\%_a$
				Accuracy	53.8%	-	52.6%	-	53.4%
18	NBA	828	30	Odds	78.4%	-	76.5%	-	78.3%
				Records	$83.7\%_a$	-	$81.5\%_b$	-	$82.6\%_{ab}$
				Accuracy	68.5%	-	67.2%	-	68.8%
19	NHL	518	31	Odds	$69.7\%_a$	-	$65.4\%_b$	-	-
				Records	79.4%	-	77.2%	-	-
				Accuracy	50.0%	-	50.3%	-	-

Note. Each row shows the average percentage of participants making wise predictions across games within each condition for that experiment. “Odds” indicates wise predictions defined as choosing the team favored by betting markets, “Records” indicates wise predictions defined as choosing the team that had won a greater percentage of games, and “Accuracy” indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at $p < .05$ using within-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979). The percentages of wise predictions defined by records are not calculated for Experiment 12 because the FIFA teams in the World Cup did not have comparable win/loss records. Experiment 3 manipulated whether the Score + Winner condition was paid based on the accuracy of their score prediction or their winner prediction; the Score + Winner column collapses across these two conditions. Experiments 4, 8, and 10 included two Relevant + Winner conditions, a condition in which participants first predicted total runs and a condition in which participants first predicted each team’s hits; the Relevant + Winner column collapses across these two conditions. The relevant predictions made in Experiments 5, 15, and 16 were total runs scored, free throws attempted by each team, and saves made by each team, respectively. Experiments 17 and 18 included two Irrelevant + Winner conditions, a condition in which participants predicted the temperature outside the indoor stadium at the start of the game and a condition where participants predicted the high temperature in the game city on July 4th 2015 (about 6 months after the game); the Irrelevant + Winner column collapses across these two conditions. The irrelevant predictions made in Experiments 5, 15 and 16 were total game time, temperature outside the stadium at game time, and percentage of U.S. citizens in the crowd, respectively. FIFA = Fédération Internationale de Football Association; MLB = Major League Baseball; NBA = National Basketball Association; NHL = National Hockey League.

Table A3 2. Participant-Level Analyses. Experiments 1-19: The average percentage of wise predictions made by participants in each prediction condition for each experiment.

Exper-iment	Sport League	# of subjects	# of games	Prediction Quality	Winner Only	Score Only	Score +Winner	Relevant +Winner	Irrelevant +Winner
				Odds	$67.2\%_a$	$60.8\%_b$	-	-	-
1	MLB	316	41	Records	$69.5\%_a$	$64.8\%_b$	-	-	-
				Accuracy	53.5%	52.4%	-	-	-
				Odds	$73.2\%_a$	$67.6\%_b$	$69.5\%_b$	-	-
2	MLB	508	39	Records	$78.7\%_a$	$72.5\%_b$	$74.7\%_b$	-	-
				Accuracy	$42.2\%_c$	$46.4\%_a$	$44.2\%_b$	-	-
				Odds	$63.4\%_a$	$57.7\%_c$	$60.2\%_b$	-	-
3	MLB	635	45	Records	$71.5\%_a$	$65.4\%_b$	$71.7\%_a$	-	-
				Accuracy	$52.6\%_a$	$51.6\%_{ab}$	$51.2\%_b$	-	-
				Odds	$70.8\%_a$	-	$66.6\%_b$	$66.7\%_b$	-
4	MLB	631	45	Records	$77.0\%_a$	-	$72.2\%_b$	$74.1\%_{ab}$	-
				Accuracy	51.8%	-	49.8%	50.0%	-
				Odds	60.1%	-	59.0%	58.8%	60.1%
5	MLB	634	42	Records	78.9%	-	77.1%	79.2%	78.6%
				Accuracy	49.2%	-	48.4%	48.7%	48.1%
				Odds	$53.5\%_a$	-	$49.6\%_b$	-	-
6	NHL	309	29	Records	$58.4\%_a$	-	$55.2\%_b$	-	-
				Accuracy	$56.8\%_a$	-	$54.2\%_b$	-	-
				Odds	$56.5\%_a$	-	$53.6\%_b$	-	-
7	MLB	337	45	Records	73.1%	-	70.5%	-	-
				Accuracy	47.1%	-	46.9%	-	-
				Odds	56.8%	-	55.8%	56.2%	-
8	MLB	625	44	Records	73.6%	-	71.3%	71.6%	-
				Accuracy	51.8%	-	51.7%	51.0%	-
				Odds	60.9%	-	59.7%	-	-
9	MLB	422	41	Records	73.4%	-	73.9%	-	-
				Accuracy	44.4%	-	45.6%	-	-
				Odds	59.4%	-	58.5%	58.5%	-
10	MLB	728	45	Records	77.3%	-	75.1%	76.2%	-
				Accuracy	54.4%	-	54.8%	54.8%	-
				Odds	$63.4\%_a$	-	$61.6\%_b$	-	-
11	MLB	525	42	Records	71.6%	-	70.6%	-	-
				Accuracy	46.6%	-	47.0%	-	-

(table continued on next page)

Exper-iment	Sport League	# of subjects	# of games	Prediction Quality	Winner Only	Score Only	Score +Winner	Relevant +Winner	Irrelevant +Winner
				Odds	61.2%$_a$	-	57.7%$_b$	-	-
12	FIFA	622	48	Records	-	-	-	-	-
				Accuracy	49.6%$_a$	-	48.4%$_b$	-	-
				Odds	70.3%	-	70.7%	-	-
13	NBA	420	32	Records	79.2%	-	77.8%	-	-
				Accuracy	62.2%	-	61.6%	-	-
				Odds	69.9%	-	70.9%	-	-
14	NHL	541	32	Records	82.0%	-	81.2%	-	-
				Accuracy	55.3%	-	55.9%	-	-
				Odds	74.2%	-	72.9%	72.4%	72.7%
15	NBA	775	32	Records	86.2%	-	84.6%	83.7%	83.4%
				Accuracy	60.3%	-	61.0%	60.4%	59.8%
				Odds	73.3%	-	72.2%	71.4%	73.0%
16	NHL	711	30	Records	81.6%	-	80.4%	78.0%	79.1%
				Accuracy	55.2%	-	54.7%	54.4%	56.0%
				Odds	74.9%$_a$	-	70.2%$_b$	-	75.0%$_a$
17	NHL	811	31	Records	83.7%$_a$	-	79.9%$_b$	-	83.2%$_a$
				Accuracy	54.0%$_a$	-	52.4%$_b$	-	53.5%$_{ab}$
				Odds	78.4%	-	76.5%	-	78.2%
18	NBA	828	30	Records	83.7%	-	81.5%	-	82.4%
				Accuracy	68.5%	-	67.2%	-	68.8%
				Odds	69.7%$_a$	-	64.5%$_b$	-	-
19	NHL	518	31	Records	79.4%$_a$	-	76.4%$_b$	-	-
				Accuracy	49.9%	-	50.8%	-	-

Note. Each row shows the average percentage of wise predictions made by participants in each condition for that experiment. “Odds” indicates wise predictions defined as choosing the team favored by betting markets, “Records” indicates wise predictions defined as choosing the team that had won a greater percentage of games, and “Accuracy” indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at $p < .05$ using between-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979). The percentages of wise predictions defined by records are not calculated for Experiment 12 because the FIFA teams in the World Cup did not have comparable win/loss records. Experiment 3 manipulated whether the Score + Winner condition was paid based on the accuracy of their score prediction or their winner prediction; the Score + Winner column collapses across these two conditions. Experiments 4, 8, and 10 included two Relevant + Winner conditions, a condition in which participants first predicted total runs and a condition in which participants first predicted each team’s hits; the Relevant + Winner column collapses across these two conditions. The relevant predictions made in Experiments 5, 15, and 16 were total runs scored, free throws attempted by each team, and saves made by each team, respectively. Experiments 17 and 18 included two Irrelevant + Winner conditions, a condition in which participants predicted the temperature outside the indoor stadium at the start of the game and a condition where participants predicted the high temperature in the game city on July 4th 2015 (about 6 months after the game); the Irrelevant + Winner column collapses across these two conditions. The irrelevant predictions made in Experiments 5, 15 and 16 were total game time, temperature outside the stadium at game time, and percentage of U.S. citizens in the crowd, respectively. FIFA = Fédération Internationale de Football Association; MLB = Major League Baseball; NBA = National Basketball Association; NHL = National Hockey League.

Table A3 3. Prediction-Level Analyses. Experiments 1-19: The percentage of wise predictions made in each prediction condition for each experiment.

Exp #	Sport League	# of subjects	# of games	Prediction Quality	Winner Only	Score Only	Score +Winner	Relevant +Winner	Irrelevant +Winner
				Odds	$67.3\%_a$	$61.4\%_b$	-	-	-
1	MLB	316	41	Records	$69.5\%_a$	$65.1\%_b$	-	-	-
				Accuracy	53.5%	52.4%	-	-	-
				Odds	$73.3\%_a$	$67.4\%_c$	$69.8\%_b$	-	-
2	MLB	508	39	Records	$78.8\%_a$	$72.5\%_c$	$75.0\%_b$	-	-
				Accuracy	$42.2\%_c$	$46.4\%_a$	$44.3\%_b$	-	-
				Odds	$63.4\%_a$	$57.6\%_c$	$60.2\%_b$	-	-
3	MLB	635	45	Records	$71.6\%_a$	$65.3\%_b$	$71.8\%_a$	-	-
				Accuracy	52.7%	51.5%	51.1%	-	-
				Odds	$70.8\%_a$	-	$66.6\%_b$	$66.8\%_b$	-
4	MLB	631	45	Records	$76.9\%_a$	-	$72.2\%_c$	$74.0\%_b$	-
				Accuracy	$51.9\%_a$	-	$49.8\%_b$	$50.0\%_b$	-
				Odds	60.2%	-	58.8%	58.8%	60.2%
5	MLB	634	42	Records	$78.9\%_a$	-	$76.8\%_b$	$79.2\%_a$	$78.9\%_a$
				Accuracy	49.2%	-	48.5%	48.8%	48.3%
				Odds	$53.5\%_a$	-	$49.8\%_b$	-	-
6	NHL	309	29	Records	$58.4\%_a$	-	$55.4\%_b$	-	-
				Accuracy	$56.8\%_a$	-	$54.3\%_b$	-	-
				Odds	$56.6\%_a$	-	$53.9\%_b$	-	-
7	MLB	337	45	Records	$73.1\%_a$	-	$70.4\%_b$	-	-
				Accuracy	47.2%	-	47.1%	-	-
				Odds	56.8%	-	55.8%	56.0%	-
8	MLB	625	44	Records	$73.6\%_a$	-	$71.2\%_b$	$71.5\%_b$	-
				Accuracy	51.8%	-	51.6%	51.1%	-
				Odds	60.9%	-	59.8%	-	-
9	MLB	422	41	Records	73.4%	-	74.1%	-	-
				Accuracy	44.4%	-	45.8%	-	-
				Odds	59.4%	-	58.6%	58.6%	-
10	MLB	728	45	Records	$77.4\%_a$	-	$75.2\%_b$	$76.2\%_{ab}$	-
				Accuracy	54.5%	-	54.8%	54.8%	-
				Odds	$63.4\%_a$	-	$61.8\%_b$	-	-
11	MLB	525	42	Records	71.6%	-	70.5%	-	-
				Accuracy	46.6%	-	46.8%	-	-

(table continued on next page)

Exp #	Sport League	# of subjects	# of games	Prediction Quality	Winner Only	Score Only	Score +Winner	Relevant +Winner	Irrelevant +Winner
				Odds	61.2%$_a$	-	57.8%$_b$	-	-
12	FIFA	622	48	Records	-	-	-	-	-
				Accuracy	49.7%$_a$	-	48.4%$_b$	-	-
				Odds	70.3%	-	70.9%	-	-
13	NBA	420	32	Records	79.1%	-	77.8%	-	-
				Accuracy	62.1%	-	61.6%	-	-
				Odds	70.0%	-	70.8%	-	-
14	NHL	541	32	Records	82.0%	-	81.4%	-	-
				Accuracy	55.4%	-	56.0%	-	-
				Odds	74.1%	-	72.9%	72.4%	72.6%
15	NBA	775	32	Records	86.2%$_a$	-	84.6%$_{ab}$	83.7%$_b$	83.4%$_b$
				Accuracy	60.2%	-	60.8%	60.3%	59.5%
				Odds	73.3%	-	72.4%	71.4%	73.0%
16	NHL	711	30	Records	81.6%$_a$	-	80.6%$_{ab}$	78.0%$_c$	79.2%$_{bc}$
				Accuracy	55.2%	-	54.6%	54.4%	55.8%
				Odds	74.8%$_a$	-	70.8%$_b$	-	75.1%$_a$
17	NHL	811	31	Records	83.6%$_a$	-	80.3%$_b$	-	83.4%$_a$
				Accuracy	53.8%	-	52.6%	-	53.4%
				Odds	78.4%$_a$	-	76.5%$_b$	-	78.3%$_a$
18	NBA	828	30	Records	83.7%$_a$	-	81.5%$_b$	-	82.6%$_{ab}$
				Accuracy	68.5%	-	67.2%	-	68.8%
				Odds	69.7%$_a$	-	65.4%$_b$	-	-
19	NHL	518	31	Records	79.4%$_a$	-	77.2%$_b$	-	-
				Accuracy	50.0%	-	50.3%	-	-

Note. Each row shows the percentage of wise predictions made in each prediction condition for that experiment. “Odds” indicates wise predictions defined as choosing the team favored by betting markets, “Records” indicates wise predictions defined as choosing the team that had won a greater percentage of games, and “Accuracy” indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at $p < .05$ using pairwise proportion tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979). The percentages of wise predictions defined by records are not calculated for Experiment 12 because the FIFA teams in the World Cup did not have comparable win/loss records. Experiment 3 manipulated whether the Score + Winner condition was paid based on the accuracy of their score prediction or their winner prediction; the Score + Winner column collapses across these two conditions. Experiments 4, 8, and 10 included two Relevant + Winner conditions, a condition in which participants first predicted total runs and a condition in which participants first predicted each team’s hits; the Relevant + Winner column collapses across these two conditions. The relevant predictions made in Experiments 5, 15, and 16 were total runs scored, free throws attempted by each team, and saves made by each team, respectively. Experiments 17 and 18 included two Irrelevant + Winner conditions, a condition in which participants predicted the temperature outside the indoor stadium at the start of the game and a condition where participants predicted the high temperature in the game city on July 4th 2015 (about 6 months after the game); the Irrelevant + Winner column collapses across these two conditions. The irrelevant predictions made in Experiments 5, 15 and 16 were total game time, temperature outside the stadium at game time, and percentage of U.S. citizens in the crowd, respectively. FIFA = Fédération Internationale de Football Association; MLB = Major League Baseball; NBA = National Basketball Association; NHL = National Hockey League.

Does predicting scores make winner predictions worse?

The tables in this section report alternative analyses for the result reported in the main text that predicting scores in addition to predicting winning teams yields worse winning team predictions than only predicting winning teams.

Table A3 4. Game-Level Analyses. Experiments 2-19: The average percentage of participants making wise predictions in the Winner and Score + Winner conditions.

Prediction Quality	Winner Only	Score + Winner
Odds	$65.4\%_a$	$63.3\%_b$
Records	$75.9\%_a$	$74.2\%_b$
Accuracy	52.3%	51.9%

Note. Each row shows the average percentage of participants making wise predictions in each condition across all games in all experiments that included a Score + Winner condition. “Odds” indicates wise predictions defined as choosing the team favored by betting markets, “Records” indicates wise predictions defined as choosing the team that had won a greater percentage of games, and “Accuracy” indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at $p < .05$ using within-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979).

Table A3 5. Participant-Level Analyses. Experiments 2-19: The average percentage of wise predictions made by participants in the Winner and Score + Winner conditions.

Prediction Quality	Winner Only	Score + Winner
Odds	67.1%$_a$	64.9%$_b$
Records	77.4%$_a$	75.8%$_b$
Accuracy	53.7%	53.4%

Note. Each row shows the average percentage of wise predictions made by participants in each condition across all games in all experiments that included a Score + Winner condition. To account for both observed and unobserved differences between experiments, the means for each condition are mean-centered by experiment and added to the overall average across all experiments and conditions. "Odds" indicates wise predictions defined as choosing the team favored by betting markets, "Records" indicates wise predictions defined as choosing the team that had won a greater percentage of games, and "Accuracy" indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at $p < .05$ using between-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979).

Table A3 6. Prediction-Level Analyses. Experiments 2-19: The percentage of wise predictions made in the Winner and Score + Winner conditions.

Prediction Quality	Winner Only	Score + Winner
Odds	66.2%$_a$	64.1%$_b$
Records	76.8%$_a$	75.4%$_b$
Accuracy	53.1%$_a$	52.7%$_b$

Note. Each row shows the percentage wise predictions made in each condition across all games in all experiments that included a Score + Winner condition. To account for both observed and unobserved differences between games, the means for each condition are mean-centered by game and added to the overall average across all games and conditions. "Odds" indicates wise predictions defined as choosing the team favored by betting markets, "Records" indicates wise predictions defined as choosing the team that had won a greater percentage of games, and "Accuracy" indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at $p < .05$ using within-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979).

Does predicting other event details make predictions worse?

The tables in this section report alternative analyses for the data presented in Figure 3 in the main text showing that making other kinds of detailed predictions that are relevant to the game also negatively affected prediction quality.

Table A3 7. Game-Level Analyses. Experiments 4, 5, 8, 10, 15, and 16: The average percentage of participants making wise predictions in the Winner, Score + Winner, and Relevant + Winner conditions.

Prediction Quality	Winner Only	Score + Winner	Relevant + Winner
Odds	64.9%$_a$	63.2%$_b$	63.1%$_b$
Records	78.6%$_a$	76.1%$_b$	6.6%$_b$
Accuracy	53.4%	52.9%	52.8%

Note. Each row shows the average percentage of participants making wise predictions in each condition across all games in all experiments that included a Relevant + Winner condition. "Odds" indicates wise predictions defined as choosing the team favored by betting markets, "Records" indicates wise predictions defined as choosing the team that had won a greater percentage of games, and "Accuracy" indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at p < .05 using within-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979).

Table A3 8. Participant-Level Analyses. Experiments 4, 5, 8, 10, 15, and 16: The average percentage of wise predictions made by participants in the Winner, Score + Winner, and Relevant + Winner conditions.

Prediction Quality	Winner Only	Score + Winner	Relevant + Winner
Odds	66.0%$_a$	64.5%$_b$	64.4%$_b$
Records	79.4%$_a$	77.1%$_b$	77.4%$_b$
Accuracy	54.1%	53.7%	53.5%

Note. Each row shows the average percentage of wise predictions made by participants in each condition across all games in all experiments that included a Relevant + Winner condition. To account for both observed and unobserved differences between experiments, the means for each condition are mean-centered by experiment and added to the overall average across all experiments and conditions. “Odds” indicates wise predictions defined as choosing the team favored by betting markets, “Records” indicates wise predictions defined as choosing the team that had won a greater percentage of games, and “Accuracy” indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at $p < .05$ using between-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979).

Table A3 9. Prediction-Level Analyses. Experiments 4, 5, 8, 10, 15, and 16: The percentage of wise predictions made in the Winner, Score + Winner, and Relevant + Winner conditions.

Prediction Quality	Winner Only	Score + Winner	Relevant + Winner
Odds	65.2%$_a$	63.6%$_b$	63.5%$_b$
Records	78.8%$_a$	76.4%$_c$	76.9%$_b$
Accuracy	53.7%	53.2%	53.1%

Note. Each row shows the percentage of wise predictions made in each condition across all games in all experiments that included a Relevant + Winner condition. To account for both observed and unobserved differences between games, the means for each condition are mean-centered by game and added to the overall average across all games and conditions. “Odds” indicates wise predictions defined as choosing the team favored by betting markets, “Records” indicates wise predictions defined as choosing the team that had won a greater percentage of games, and “Accuracy” indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at $p < .05$ using within-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979).

Are predictions worse because people pay less attention?

The tables in this section report alternative analyses for the data presented in Figure 4 in the main text showing that making detailed prediction that are irrelevant to the game did not affect prediction quality.

Table A3 10. Game-Level Analyses. Experiments 5 and 15-18: The average percentage of participants making wise predictions in the Winner, Score + Winner, and Irrelevant + Winner conditions.

Prediction Quality	Winner Only	Score + Winner	Irrelevant + Winner
Odds	71.2%$_a$	69.4%$_b$	71.0%$_a$
Records	82.6%$_a$	80.6%$_b$	81.4%$_b$
Accuracy	56.8%	56.1%	56.5%

Note. Each row shows the average percentage of participants making wise predictions in each condition across all games in all experiments that included an Irrelevant + Winner condition. "Odds" indicates wise predictions defined as choosing the team favored by betting markets, "Records" indicates wise predictions defined as choosing the team that had won a greater percentage of games, and "Accuracy" indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at $p < .05$ using within-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979).

Table A3 11. Participant-Level Analyses. Experiments 5 and 15-18: The average percentage of wise predictions made by participants in the Winner, Score + Winner, and Irrelevant + Winner conditions.

Prediction Quality	Winner Only	Score + Winner	Irrelevant + Winner
Odds	$72.7\%_a$	$70.6\%_b$	$72.4\%_a$
Records	$83.0\%_a$	$80.9\%_b$	$81.6\%_b$
Accuracy	57.9%	57.2%	57.8%

Note. Each row shows the average percentage of wise predictions made by participants in each condition across all games in all experiments that included an Irrelevant + Winner condition. To account for both observed and unobserved differences between experiments, the means for each condition are mean-centered by experiment and added to the overall average across all experiments and conditions. “Odds” indicates wise predictions defined as choosing the team favored by betting markets, “Records” indicates wise predictions defined as choosing the team that had won a greater percentage of games, and “Accuracy” indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at $p < .05$ using between-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979).

Table A3 12. Prediction-Level Analyses. Experiments 5 and 15-18: The percentage of wise predictions made in the Winner, Score + Winner, and Irrelevant + Winner conditions.

Prediction Quality	Winner Only	Score + Winner	Irrelevant + Winner
Odds	$71.9\%_a$	$70.0\%_b$	$71.7\%_a$
Records	$82.8\%_a$	$80.8\%_c$	$81.7\%_b$
Accuracy	57.4%	56.7%	57.2%

Note. Each row shows the percentage of making wise predictions made in each condition across all games in all experiments that included an Irrelevant + Winner condition. To account for both observed and unobserved differences between games, the means for each condition are mean-centered by game and added to the overall average across all games and conditions. “Odds” indicates wise predictions defined as choosing the team favored by betting markets, “Records” indicates wise predictions defined as choosing the team that had won a greater percentage of games, and “Accuracy” indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at $p < .05$ using within-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979).

Are predictions worse because people think harder?

The tables in this section report alternative analyses for the data presented in Figure 5 in the main text showing that incentivizing people to think harder about their predictions did not negatively affect winning team prediction quality, although having them predict scores did.

Table A3 13. Game-Level Analyses. Experiments 13, 14, and 19: The average percentage of participants making wise predictions in the Winner and Score + Winner conditions for low- versus high-incentives.

Prediction Quality	Winner Only low incentive	Winner Only high incentive	Score + Winner low incentive	Score + Winner high incentive
Odds	70.1%$_{a}$	70.0%$_{ab}$	68.7%$_{c}$	69.2%$_{bc}$
Records	79.2%$_{b}$	80.7%$_{a}$	77.7%$_{c}$	79.3%$_{b}$
Accuracy	55.9%$_{ab}$	56.0%$_{ab}$	56.4%$_{a}$	55.5%$_{b}$

Note. Each row shows the average percentage of participants making wise predictions in each condition across all games in all experiments that varied incentives for accuracy within-subjects. “Odds” indicates wise predictions defined as choosing the team favored by betting markets, “Records” indicates wise predictions defined as choosing the team that had won a greater percentage of games, and “Accuracy” indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at $p < .05$ using within-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979).

Table A3 14. Participant-Level Analyses. Experiments 13, 14, and 19: The average percentage of wise predictions made by participants in the Winner and Score + Winner conditions for low- versus high-incentives.

Prediction Quality	Winner Only low incentive	Winner Only high incentive	Score + Winner low incentive	Score + Winner high incentive
Odds	70.0%	69.7%	68.5%	68.7%
Records	79.4%	80.8%	78.0%	79.4%
Accuracy	55.3%	55.3%	56.0%	55.1%

Note. Each row shows the average percentage of wise predictions made by participants in each condition across all games in all experiments that varied incentives for accuracy within-subjects. To account for both observed and unobserved differences between experiments, the means for each condition are mean-centered by experiment and added to the overall average across all experiments and conditions. "Odds" indicates wise predictions defined as choosing the team favored by betting markets, "Records" indicates wise predictions defined as choosing the team that had won a greater percentage of games, and "Accuracy" indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at $p < .05$ using between-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979).

Table A3 15. Prediction-Level Analyses. Experiments 13, 14, and 19: The percentage of wise predictions made in the Winner and Score + Winner conditions for low- versus high-incentives.

Prediction Quality	Winner low incentive	Winner high incentive	Score + Winner low incentive	Score + Winner high incentive
Odds	70.0%	69.9%	68.8%	69.0%
Records	79.5%$_b$	81.0%$_a$	78.2%$_c$	79.7%$_b$
Accuracy	55.4%	55.6%	56.0%	55.3%

Note. Each row shows the percentage of making wise predictions made in each condition across all games in all experiments that varied incentives for accuracy within-subjects. To account for both observed and unobserved differences between games, the means for each condition are mean-centered by game and added to the overall average across all games and conditions. "Odds" indicates wise predictions defined as choosing the team favored by betting markets, "Records" indicates wise predictions defined as choosing the team that had won a greater percentage of games, and "Accuracy" indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at $p < .05$ using within-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979).

Are predictions worse because people think less globally or more locally?

Only a single measure of overall global and local considerations was collected per person, so these results cannot be analyzed at the game-level or prediction-level.

Do people who make detailed predictions use useful information less?

The tables in this section report alternative analyses for the data presented in Tables 2 and 3 in the main text showing the weights given to win/loss records and home field in winning team predictions.

Table A3 16. Game-Level Analyses. Experiments 1-5, 7-11, and 13-19: The change in the percentage of participants in the Winner condition choosing the team to win based on win/loss records and home field advantage.

Coefficients	Winner Only	
better record	0.355	***
home team	0.125	***
| record difference |	-0.587	***
better record * | record difference |	1.565	***
home team * | record difference |	-0.451	***

Note. * p < .05, ** p < .01, *** p < .001. Weights are estimated using Ordinary Least Squares regression. Because each game generates two observations (one for each team) standard errors are clustered by game.

Table A3 17. Participant-Level Analyses. Experiments 1-5, 7-11, and 13-19: The average weights participants in the Winner condition gave to win/loss records and home field advantage.

Coefficients	Winner Only	
better record	0.170	***
home team	0.136	***
| record difference |	-3.302	***
better record * | record difference |	2.522	***
home team * | record difference |	-1.172	***

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Average marginal weights are estimated by using logistic regressions to estimate marginal weights for each participant in each experiment and averaging marginal weights across participants within conditions. Because each participant generates two observations per prediction (one for each team) standard errors for each participant's weights are clustered by participant-game.

Table A3 18. Prediction-Level Analyses. Experiments 1-5, 7-11, and 13-19: The weights given to win/loss records and home field advantage in the Winner condition.

Coefficients	Winner Only	
better record	0.265	***
home team	0.153	***
| record difference |	-1.544	***
better record * | record difference |	3.418	***
home team * | record difference |	-0.448	***

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Marginal weights are estimated using logistic regression. Because each prediction generates two observations (one for each team) standard errors are clustered by experiment-participant-game.

Table A3 19. Game-Level Analyses. Experiments 1-5, 7-11, and 13-19: Differences from the Winner condition in the change in the percentage of participants choosing the team to win based on win/loss records and home field advantage.

Coefficients	Score[†]		Relevant		Irrelevant	
better record	-0.058	***	-0.029	***	-0.002	
home team	-0.073	***	-0.053	***	0.032	**
| record difference |	-0.104	***	-0.034		0.064	***
better record * | record difference |	0.036		-0.112	**	-0.132	***
home team * | record difference |	0.181	***	0.188	***	0.004	
Number of participants in sample	5,537		1,958		1,541	
Number of games in sample	644		235		162	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. [†]Score includes all conditions where participants predicted the final score. Weights are estimated using Ordinary Least Squares regression. Because each game generates two observations (one for each team) standard errors are clustered by game.

Table A3 20. Participant-Level Analyses. Experiments 1-5, 7-11, and 13-19: Differences from the Winner condition in the average weights given to win/loss records and home field advantage.

Coefficients	Score[†]		Relevant		Irrelevant	
better record	-0.058	***	-0.020		0.035	
home team	-0.116	***	-0.079	***	0.037	
| record difference |	0.149		0.237		-0.033	
better record * | record difference |	-0.677	**	-0.513		-0.419	
home team * | record difference |	0.381	***	0.036		0.448	
Number of participants in sample	5,537		1,958		1,541	
Number of games in sample	644		235		162	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. [†]Score includes all conditions where participants predicted the final score. Average marginal weights are estimated by using logistic regressions to estimate marginal weights for each participant in each experiment and averaging marginal weights across participants within conditions. Because each participant generates two observations per prediction (one for each team) standard errors for each participant's weights are clustered by participant-game.

Table A3 21. Prediction-Level Analyses. Experiments 1-5, 7-11, and 13-19: Differences from the Winner condition in the weights given to win/loss records and home field advantage.

Coefficients	Score†		Relevant		Irrelevant	
better record	-0.068	***	-0.018		0.037	*
home team	-0.120	***	-0.077	***	0.056	**
| record difference |	-0.009		0.221	*	0.281	***
better record * | record difference |	-0.169	**	-0.583	***	-0.583	***
home team * | record difference |	0.231	***	0.180		0.067	
Number of participants in sample	5,537		1,958		1,541	
Number of games in sample	644		235		162	

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. †Score includes all conditions where participants predicted the final score. Marginal weights are estimated using logistic regression. Because each prediction generates two observations (one for each team) standard errors are clustered by experiment-participant-game.

Which games will show the effect?

The tables in this section report alternative analyses for the data presented in Figure 8 in the main text showing that making relevant detailed predictions had a considerably larger negative effect on prediction quality when both cues agreed (the home team had the better record) than when they disagreed (the visiting team had the better record).

Table A3 22. Game-Level Analyses. Experiments 1-19: The percentage of participants making wise predictions by prediction condition and which team had the better record.

	Visiting Team Has Better Record		Home Team Has Better Record	
Prediction Quality	Winner & Irrelevant	Score & Relevant	Winner & Irrelevant	Score & Relevant
Odds	55.5%$_c$	54.7%$_d$	79.0%$_a$	74.6%$_b$
Records	72.4%$_c$	72.8%$_c$	81.4%$_a$	76.4%$_b$
Accuracy	51.3%	51.2%	54.4%	54.0%

Note. Each row shows the average percentage of participants making wise predictions in each condition across all games in all experiments. “Odds” indicates wise predictions defined as choosing the team favored by betting markets, “Records” indicates wise predictions defined as choosing the team that had won a greater percentage of games, and “Accuracy” indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at $p < .05$ using within-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979).

Table A3 23. Participant-Level Analyses. Experiments 1-19: The average percentage of wise predictions made by participants by prediction condition and which team had the better record.

Prediction Quality	Visiting Team Has Better Record: Winner & Irrelevant	Visiting Team Has Better Record: Score & Relevant	Home Team Has Better Record: Winner & Irrelevant	Home Team Has Better Record: Score & Relevant
Odds	55.5%$_c$	54.8%$_d$	78.2%$_a$	74.2%$_b$
Records	73.1%$_c$	73.6%$_c$	80.7%$_a$	75.9%$_b$
Accuracy	51.2%	51.2%	54.0%	53.7%

Note. Each row shows the average percentage of wise predictions made by participants in each condition across all games in all experiments. To account for both observed and unobserved differences between experiments, the means for each condition are mean-centered by experiment and added to the overall average across all experiments and conditions. "Odds" indicates wise predictions defined as choosing the team favored by betting markets, "Records" indicates wise predictions defined as choosing the team that had won a greater percentage of games, and "Accuracy" indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at $p < .05$ using between-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979).

Table A3 24. Prediction-Level Analyses. Experiments 1-19: The percentage of wise predictions made by prediction condition and which team had the better record.

Prediction Quality	Visiting Team Has Better Record: Winner & Irrelevant	Visiting Team Has Better Record: Score & Relevant	Home Team Has Better Record: Winner & Irrelevant	Home Team Has Better Record: Score & Relevant
Odds	55.5%$_c$	54.8%$_d$	79.3%$_a$	75.8%$_b$
Records	73.0%$_c$	73.4%$_c$	81.6%$_a$	77.4%$_b$
Accuracy	51.1%	51.1%	55.5%	55.1%

Note. Each row shows the percentage of making wise predictions made in each condition across all games in all experiments. To account for both observed and unobserved differences between games, the means for each condition are mean-centered by game and added to the overall average across all games and conditions. "Odds" indicates wise predictions defined as choosing the team favored by betting markets, "Records" indicates wise predictions defined as choosing the team that had won a greater percentage of games, and "Accuracy" indicates wise predictions defined as choosing the team that actually won the game. Within each row, means with different subscripts differ at $p < .05$ using within-subjects pairwise t-tests and the Holm-Bonferroni correction for multiple comparisons (Holm, 1979).

REFERENCES

Bastardi, A., & Shafir, E. (1998). On the pursuit and misuse of useless information. *Journal of Personality and Social Psychology*, *75*(1), 19-32.

Brehmer, B. (1972). Cue utilization and cue consistency in multiple-cue probability learning. *Organizational Behavior and Human Performance*, *8*(2), 286-296.

Buehler, R., & Griffin, D. (2003). Planning, personality, and prediction: The role of future focus in optimistic time predictions. *Organizational Behavior and Human Decision Processes*, *92*(1), 80-90.

Buehler, R., Griffin, D., & Ross, M. (1994). Exploring the "planning fallacy": Why people underestimate their task completion times. *Journal of Personality and Social Psychology*, *67*(3), 366-381.

Brunswik, E., & Kamiya, J. (1953). Ecological cue-validity of'proximity'and of other Gestalt factors. *The American Journal of Psychology*, *66*(1), 20-32.

Cousineau, D. (2005). Confidence intervals in within-subject designs: A simpler solution to Loftus and Masson’s method. *Tutorials in Quantitative Methods for Psychology*, *1*(1), 42-45.

Dana, J., Dawes, R., & Peterson, N. (2013). Belief in the unstructured interview: The persistence of an illusion. *Judgment and Decision Making*, *8*(5), 512-520.

Dawes, R. M. (1996). *House of cards: Psychology and psychotherapy built on myth*. New York: Free Press.

Dijksterhuis, A., Bos, M. W., Nordgren, L. F., & Van Baaren, R. B. (2006). On making the right choice: The deliberation-without-attention effect. *Science*, *311*(5763), 1005-1007.

Dijksterhuis, A., Bos, M. W., Van der Leij, A., & Van Baaren, R. B. (2009). Predicting soccer matches after unconscious and conscious thought as a function of expertise. *Psychological Science*, *20*(11), 1381-1387.

Dube-Rioux, L., & Russo, J. E. (1988). An availability bias in professional judgment. *Journal of Behavioral Decision Making*, *1*(4), 223-237.

Dunning, D. (2007). Prediction: The inside view. In E. T. Higgins & A. Kruglanski (Eds.), *Social psychology: Handbook of basic principles* (2nd ed., pp. 69-90). New York: Guilford.

Edgell, S. E., Castellan Jr, N. J., Roe, R. M., Barnes, J. M., Ng, P. C., Bright, R. D., & Ford, L. A. (1996). Irrelevant information in probabilistic categorization.*Journal of Experimental Psychology: Learning, Memory, and Cognition*, *22*(6), 1463-1481.

Feldman, J. M., & Lynch, J. G. (1988). Self-generated validity and other effects of measurement on belief, attitude, intention, and behavior. *Journal of Applied Psychology*, *73*(3), 421-435.

Fischhoff, B., Slovic, P., & Lichtenstein, S. (1978). Fault trees: Sensitivity of estimated failure probabilities to problem representation. *Journal of Experimental Psychology: Human Perception and Performance*, *4*(2), 330-344.

Griffin, D., & Tversky, A. (1992). The weighing of evidence and the determinants of confidence. *Cognitive Psychology*, *24*(3), 411-435.

Grove, W. M., & Meehl, P. E. (1996). Comparative efficiency of informal (subjective, impressionistic) and formal (mechanical, algorithmic) prediction procedures: The clinical–statistical controversy. *Psychology, Public Policy, and Law*, *2*(2), 293-323.

Grove, W. M., Zald, D. H., Lebow, B. S., Snitz, B. E., & Nelson, C. (2000). Clinical versus mechanical prediction: A meta-analysis. *Psychological Assessment*, *12*(1), 19-30.

Hackenbrack, K. (1992). Implications of seemingly irrelevant evidence in audit judgment. *Journal of Accounting Research, 30*(1), 126-136.

Hall, C. C., Ariss, L., & Todorov, A. (2007). The illusion of knowledge: When more information reduces accuracy and increases confidence. *Organizational Behavior and Human Decision Processes*, *103*(2), 277-290.

Helzer, E. G., & Dunning, D. (2012). Why and when peer prediction is superior to self-prediction: The weight given to future aspiration versus past achievement. *Journal of Personality and Social Psychology*, *103*(1), 38-53.

Hoffman, V. B., & Patton, J. M. (1997). Accountability, the dilution effect, and conservatism in auditors' fraud judgments. *Journal of Accounting Research*, 227-237.

Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics, 30*(1), 65-70.

Hutchinson, J. W., & Alba, J. W. (1991). Ignoring irrelevant information: Situational determinants of consumer learning. *Journal of Consumer Research 18*(3), 325-345.

Kahneman, D., & Lovallo, D. (1993). Timid choices and bold forecasts: A cognitive perspective on risk taking. *Management Science, 39*(1), 17-31.

Kahneman, D., & Tverskty, A. (1972). Subjective probability: A judgment of representativeness. *Cognitive Psychology, 3*(3), 430-454.

Kahneman, D., & Tversky, A. (1973). On the psychology of prediction. *Psychological Review*, *80*(4), 237-251.

Kahneman, D., & Tversky, A. (1982). The simulation heuristic. In D. Kahneman, P. Slovic, & A. Tversky (Eds.), *Judgment under uncertainty: Heuristics and biases* (pp. 201-208). New York: Cambridge.

Keeley, S. M., & Doherty, M. E. (1972). Bayesian and regression modeling of graduate admission policy. *Organizational Behavior and Human Performance, 8*(2), 297-323.

Labella, C., & Koehler, D. J. (2004). Dilution and confirmation of probability judgments based on nondiagnostic evidence. *Memory & Cognition, 32*(7), 1076-1089.

Lagnado, D., & Sloman, S. A. (2004). Inside and outside probability judgment. In D. J. Koehler & N. Harvey (Eds.), *The Blackwell handbook of judgment and decision making* (pp. 157-176). Malden, MA: Blackwell.

Lichtenstein, S., Earle, T. C., & Slovic, P. (1975). Cue utilization in a numerical prediction task. *Journal of Experimental Psychology: Human Perception and Performance*, *1*(1), 77-85.

Lovallo, D., & Kahneman, D. (2003). Delusions of success: How optimism undermines executives' decisions. *Harvard Business Review, 81*(7), 56-63.

Lynch Jr, J. G., Marmorstein, H., & Weigold, M. F. (1988). Choices from sets including remembered brands: Use of recalled attributes and prior overall evaluations. *Journal of Consumer Research, 15*(2), 169-184.

Meehl, P. E. (1954). *Clinical versus statistical prediction: A theoretical analysis and a review of the evidence*. Minneapolis: University of Minnesota Press.

Menon, G., & Raghubir, P. (2003). Ease-of-retrieval as an automatic input in judgments: A mere-accessibility framework?. *Journal of Consumer Research,30*(2), 230-243.

Menon, G., Raghubir, P., & Schwarz, N. (1995). Behavioral frequency judgments: An accessibility-diagnosticity framework. *Journal of Consumer Research*, 212-228.

Mertz, W. H., & Doherty, M. E. (1974). The influence of task characteristics on strategies of cue combination. *Organizational Behavior and Human Performance*, *12*(2), 196-216.

Meyvis, T., & Janiszewski, C. (2002). Consumers' beliefs about product benefits: The effect of obviously irrelevant product information. *Journal of Consumer Research*, *28*(4), 618-635.

Morewedge, C. K., & Todorov, A. (2012). The least likely act: Overweighting atypical past behavior in behavioral predictions. *Social Psychological and Personality Science*, *3*(6), 760-766.

Morey, R. D. (2008). Confidence intervals from normalized data: A correction to Cousieneau (2005). *Tutorials in Quantitative Methods for Psychology*, *4*(2), 61-64.

Nelson, M. W., Bloomfield, R., Hales, J. W., & Libby, R. (2001). The effect of information strength and weight on behavior in financial markets. *Organizational Behavior and Human Decision Processes*, *86*(2), 168-196.

Nieuwenstein, M. R., Wierenga, T., Morey, R. D., Wicherts, J. M., Blom, T. N., Wagenmakers, E. J., & van Rijn, H. (2015). On making the right choice: A meta-analysis and large-scale replication attempt of the unconscious thought advantage. *Judgment and Decision Making*, *10*(1), 1-17.

Nisbett, R. E., & Wilson, T. D. (1977). Telling more than we can know: Verbal reports on mental processes. *Psychological Review*, *84*(3), 231-259.

Nisbett, R. E., Zukier, H., & Lemley, R. E. (1981). The dilution effect: Nondiagnostic information weakens the implications of diagnostic information.*Cognitive Psychology*, *13*(2), 248-277.

Pious, S. (1993). *The psychology of judgment and decision making*. New York: McGraw-Hill.

Preacher, K. J., & Kelley, K. (2011). Effect size measures for mediation models: Quantitative strategies for communicating indirect effects.*Psychological methods*, *16*(2), 93-115.

Schkade, D. A., & Kahneman, D. (1998). Does living in California make people happy? A focusing illusion in judgments of life satisfaction. *Psychological Science, 9*(5), 340-346.

Shelton, S. W. (1999). The effect of experience on the use of irrelevant evidence in auditor judgment. *The Accounting Review*, *74*(2), 217-224.

Simmons, C. J., Bickart, B. A., & Lynch Jr, J. G. (1993). Capturing and creating public opinion in survey research. *Journal of Consumer Research 20*(2), 316-329.

Simmons, C. J., & Lynch Jr, J. G. (1991). Inference effects without inference making? Effects of missing information on discounting and use of presented information. *Journal of Consumer Research, 17*(4), 477-491.

Slovic, P. (1966). Cue-consistency and cue-utilization in judgment. *The American Journal of Psychology*, *79*(3), 427-434.

Slovic, P. (1975). Choice between equally valued alternatives. *Journal of Experimental Psychology: Human Perception and Performance*, *1*(3), 280-287.

Slovic, P., & Lichtenstein, S. (1971). Comparison of Bayesian and regression approaches to the study of information processing in judgment. *Organizational Behavior and Human Performance*, *6*(6), 649-744.

Smith, H. D., Stasson, M. F., & Hawkes, W. G. (1998). Dilution in legal decision making: Effect of non-diagnostic information in relation to amount of diagnostic evidence. *Current Psychology*, *17*(4), 333-345.

Soll, J. B. (1999). Intuitive theories of information: Beliefs about the value of redundancy. *Cognitive Psychology*, *38*(2), 317-346.

Tetlock, P. E., & Boettger, R. (1989). Accountability: A social magnifier of the dilution effect. *Journal of Personality and Social Psychology*, *57*(3), 388-398.

Tetlock, P. E., Lerner, J. S., & Boettger, R. (1996). The dilution effect: Judgmental bias, conversational convention, or a bit of both?. *European Journal of Social Psychology* , *26*(6), 915-934.

Troutman, C. M., & Shanteau, J. (1977). Inferences based on nondiagnostic information. *Organizational Behavior and Human Performance*, *19*(1), 43-55.

Tversky, A., & Kahneman, D. (1971). Belief in the law of small numbers. *Psychological Bulletin*, *76*(2), 105-110.

Tversky, A., & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. *Cognitive Psychology*, *5*(2), 207-232.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. S*cience*, *185*(4157), 1124-1131.

Weaver, K., Garcia, S. M., & Schwarz, N. (2012). The presenter's paradox. *Journal of Consumer Research*, *39*(3), 445-460.

Wilson, T. D., & Gilbert, D. T. (2005). Affective forecasting knowing what to want. *Current Directions in Psychological Science*, *14*(3), 131-134.

Wilson, T. D., Wheatley, T., Meyers, J. M., Gilbert, D. T., & Axsom, D. (2000). Focalism: A source of durability bias in affective forecasting. *Journal of Personality and Social Psychology*, *78*(5), 821-836.

Yaniv, I. (2004). The benefit of additional opinions. *Current Directions in Psychological Science*, *13*(2), 75-78.

Yoon, S. O., Suk, K., Goo, J. K., Lee, J., & Lee, S. M. (2013). The devil is in the specificity: The negative effect of prediction specificity on prediction accuracy. *Psychological Science*, *24*(7), 1164-1170.

York, K. M., Doherty, M. E., & Kamouri, J. (1987). The influence of cue unreliability on judgment in a multiple cue probability learning task. *Organizational Behavior and Human Decision Processes*, *39*(3), 303-317.

Zukier, H. (1982). The dilution effect: The role of the correlation and the dispersion of predictor variables in the use of nondiagnostic information. *Journal of Personality and Social Psychology*, *43*(6), 1163-1174.