SM Note 1: Experimental Materials

Consent Form

I would like to voluntarily participate in this study.

The study will take approx. 8 minutes.

As compensation, I will receive £1 GPB as a participation fee.

I understand that I will not be purposefully misled, I will not receive incorrect or false information and feedback, and I will not be held in belief of false pretenses.

All data will be collected and saved anonymously.

I am free to discontinue participation at any time. Do you agree and consent to the above?

- I consent

- I do not consent

Study Instructions

In this study, you will be presented with a total of 20 scenarios.

In each scenario, you will be asked to consider the following hypothetical situation:

Scenario:

At work, you are tasked with choosing an investment among two alternatives. Each investment costs the same (£500,000) and, if successful, each investment would report similar earnings to your company (£1,000,000). If the investment is not successful, the company will lose the £500,000 invested.

Due to logistic reasons, the company has to choose one of the two alternative investments.

You (and everyone in your company) know the probability that investment 1 will be successful. Everyone agrees on the % probability that investment 1 will be successful.

You have no information on the probability that investment 2 will be successful. However, 4 of your co-workers have been working on estimating the probability that investment 2 will be successful. These co-workers might or might not have access to the actual probability of the investment being successful.

Your Task:

In each scenario, you will be presented with the probabilities estimated by your co-workers that investment 2 will be successful.

Then, you will have to choose between investment 1 and investment 2 for different probabilities of investment 1 being successful.

Specifically, you will be shown the following table. Each row represents a choice between investment 1 (with the stated probability of being successful) and investment 2 (with the probabilities of being successful estimated by your co-workers). You will have to choose between investment 1 and 2 in each row.

To proceed with the study, please click next:

Attention Check

Before proceeding with the study, we would like to ask you a question to ensure that you read the previous instructions:

In the following pages, you will be presented with a few scenarios about (select the one that applies):

- Choosing investments
- Risk and safety regulations at work
- Risk perceptions among motor vehicle drivers

Example of Scenario

You must choose between two investments that costs and pay the same. These are the probabilities estimated by your co-workers that investment 2 will be successful:

Probability estimated by co-worker 1: 14%

Probability estimated by co-worker 2: 25%

Probability estimated by co-worker 3: 18%

Probability estimated by co-worker 4: 22%

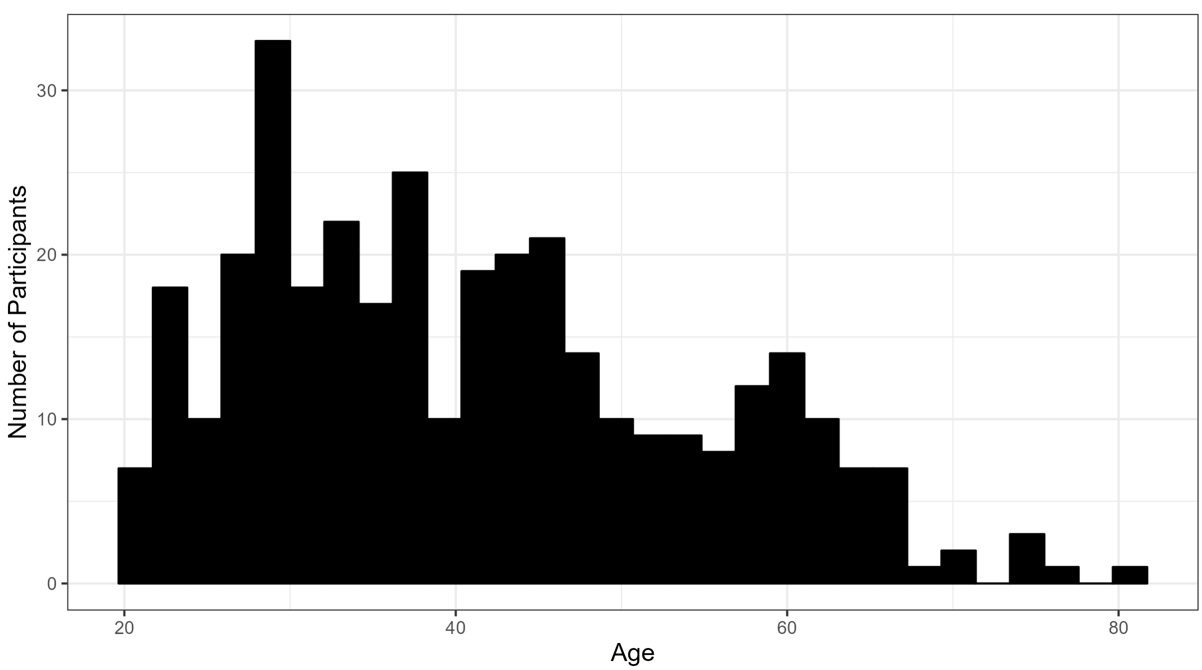
Everyone in your company (including yourself) knows and agrees on the actual probability that investment 1 will be successful. For each probability of investment 1 being successful, would you choose investment 1 or investment 2?

	Investment 1	Investment 2
Probability of investment 1 being successful: 0%	○	○
Probability of investment 1 being successful: 10%	○	○
Probability of investment 1 being successful: 20%	○	○
Probability of investment 1 being successful: 30%	○	○
Probability of investment 1 being successful: 40%	○	○
Probability of investment 1 being successful: 50%	○	○
Probability of investment 1 being successful: 60%	○	○
Probability of investment 1 being successful: 70%	○	○
Probability of investment 1 being successful: 80%	○	○
Probability of investment 1 being successful: 90%	○	○
Probability of investment 1 being successful: 100%	○	○

SM Note 2: Respondents' Demographic Characteristics

In this section, I present an overview of the demographic characteristics of the 357 participants that completed the online study. All participants were residents of the United Kingdom.

- Gender: A total of 146 participants self-identified as males (40.9%), 202 as females (56.6%). Information on gender was missing from 9 participants (2.5%).
- Ethnicity: A total of 316 participants self-identified as white (88.5%), 4 as black (1.1%), 12 as asian (3.4%), 9 as mixed (2.5%) and 4 selected the "Other" category (1.1%). Information on race was missing from 12 participants (3.4%).
- Age: The study participants had an average age of 41.2 years (SD = 13.2 years). Information on age was missing from 9 participants (2.5%).The following image presents the distribution of the participant's age.



SM Note 3: Building Assumption Tests

In this supplemental note, I present detailed results of the Linear Mixed Models testing the building assumption of my main model. Both models include participant-specific fixed effects.

The left column (Model 1) presents the estimated parameters (with standard errors in parentheses) for a linear model regressing the participant and scenario-specific measure of the subjective probability of success assigned to Investment 2 (SP) on the average probability reported by the 4 hypothetical co-workers (P).

The right column (Model 2) presents the estimated parameters (with standard errors in parentheses) for a linear model regressing the absolute size of the subjective probability deviations from the average probability reported by the 4 hypothetical co-workers (|SP - P|) on the standard deviation of the co-workers' probability estimates (SD).

Table S1:

	Dependent variable:	
	SP	|SP-P|
	(1)	(2)
P	0.813^{***}	
	(0.005)	
SD		0.135^{***}
		(0.012)
Constant	0.063^{***}	0.076^{***}
	(0.005)	(0.004)
Observations	7,140	7,140
Log Likelihood	5,985.649	8,108.648
Note:	*p<0.1; **p<0.05; ***p<0.01	

SM Note 4: Estimation Details

The full model specification is estimated using a maximum likelihood routine. This model is given by the following equation:

$$SP_{is} = p_s + (\gamma_s \alpha)(1 - p_s - p_s^{\beta}) + \epsilon_{is}$$

Where SP_{is} is the subjective probability assigned to Investment 2 being successful by participant i in scenario s, p_s and γ_s are the average and standard deviation of the co-workers' subjective probabilities, and ϵ_{is} is a zero-mean normally distributed error term with σ^2 variance. Hence, since:

$$\epsilon_{is} \sim N(0, \sigma^2)$$

Then:

$$\underbrace{[SP_{is} - p_s - (\gamma_s \alpha)(1 - p_s - p_s^{\beta})]}_{\epsilon_{is}} \sim N(0, \sigma^2)$$

This model has 3 free parameters (α, β, and σ^2). These parameters are obtained by maximising the following log-likelihood function:

$$log\ l(\alpha, \beta, \sigma^2) = \frac{-n}{2} \cdot ln(2\pi) - \frac{n}{2} \cdot ln(\sigma^2) - \frac{1}{2\sigma^2} \cdot \sum \epsilon_{is}^2$$

Where $\epsilon_{is} = SP_{is} - p_s - (\gamma_s \alpha)(1 - p_s - p_s^{\beta})$ and n equals the number of observations (n = 7,140). I estimated this model using R´s optim function and the L-BFGS-B optimization algorithm. Note that if σ^2 is equal or lower than 0, the above log likelihood is not specified. Hence, I set a minimum value of 0.0001 for σ^2. To obtain the standard errors of the parameters' estimates, I employed a cluster bootstrap approach. Specifically, I created 1000 bootstrap data sets. Each of these data sets consisted of all the data from a set 357 participants selected randomly with replacement from the set of (the 357) study participants. Then, I estimated my model

1000 times using each bootstrap data set once. Using these 1000 estimates of each model parameter, I derived the parameters' standard errors by calculating the standard deviation of the 1000 parameters' estimates.

SM Note 5: Robustness of Model Estimates to Inclusion Criteria

In this note, I demonstrate that my main model estimates remain qualitatively the same when employing less stringent data exclusion criteria. Specification 1 represents my main model specification (the one presented in the main body of the paper). In this specification, I excluded all responses from participants that at some point in the experiment 1) selected an investment with a known success probability of 0, or 2) failed to select an investment with a known success probability of 1. Specification 2 offers a different approach. Instead of eliminating all responses from participants who deviated from the above two criteria at any point, I omitted only specific responses (pertaining to certain scenarios) that demonstrated such behavior. Consequently, this specification includes responses from most participants, with some observations from certain participants being excluded. Specification 3 uses all data from all participants. To do so, I assumed the following:

- If a participant favored an investment with a confirmed success probability of 0 over an investment with an unknown probability, I inferred that the respondent assigned a subjective success probability of 0 to the unknown-probability investment.
- If a participant favored an investment with an unknown probability over an investment with a confirmed success probability of 1, I inferred that the respondent assigned a subjective success probability of 1 to the unknown-probability investment.

In essence, in both cases, I assumed that the display of inconsistent or irrational behavior was the result of the respondent's indifference between the two investment options.

In all three specifications, the model parameters were estimated by Maximum Likelihood and the standard errors obtained by following a cluster bootstrap routine (with 1000 bootstraps for each model). The estimated parameters (with standard errors in parenthesis) are presented in Table S2. Note that the qualitative properties of the estimated coefficients remain the same across specifications. Namely, across specifications 1) the alpha parameter is significantly different from 0, and 2) the beta parameter is significantly smaller than 1.

Table S2

	Specification 1	Specification 2	Specification 3
α	0.674	0.997	0.921
	(0.051)	(0.049)	(0.049)
β	0.337	0.514	0.403
	(0.045)	(0.035)	(0.045)
σ^2	0.015	0.020	0.033
	(0.001)	(0.001)	(0.002)
Observations	7,140	11,032	12,040
Individuals	357	592	602
Log Likelihood	4,777.84	5,838.29	3,431.65

SM Note 6: Model Recovery Analysis

In this supplemental note, I present the results of a model recovery analysis. To conduct this analysis, I followed these steps:

1. I considered all combinations of the following alpha and beta values:
   - $\alpha =$ (0.1 to 1 in increments of 0.1)
   - $\beta =$ (0.1 to 2 in increments of 0.1)
2. For each combination of alpha and beta values, I simulated the subjective probabilities for 357 individuals, each facing 20 scenarios (i.e., various combinations of anchors and levels of ambiguity). These 20 scenarios matched those used in the experimental elicitation (i.e., included all combinations of situations with anchors ranging from 0.2 to 0.8 in increments of 0.2, and the amount of ambiguity from 0.05 to 0.25 in increments of 0.05). To simulate the subjective probabilities assigned to an event by an individual in a given scenario, I used the following function:

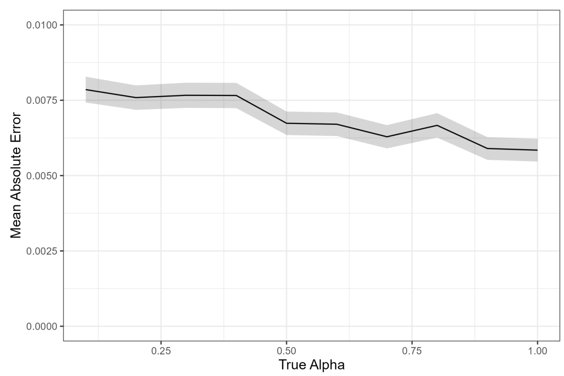
   $$SP_{is} = p_s + (\gamma_s \alpha)(1 - p_s - p_s^{\beta}) + \epsilon_{is}$$

   Where ϵ_{is} is a random draw from a normal distribution with mean 0 and SD of 0.1 (thus matching the distribution of the error term obtained in my empirical estimations), p_s is the anchoring probability in the given scenario, and γ_s the amount of ambiguity in the given scenario.
3. Using the simulated data, I estimated my main model to obtain an estimate of alpha and beta.
4. I repeated this process 100 times for each alpha and beta combination, resulting in a total of 20,000 model estimations.

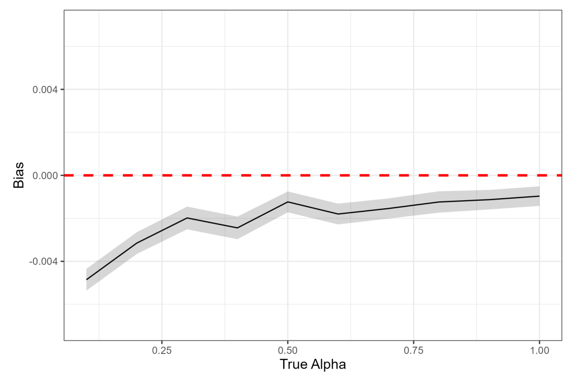
5. I aggregated the data across various alpha and beta values and calculated the mean absolute error (the average of the absolute differences between the estimated parameters and the parameters used to create the simulated subjective probabilities) for both alpha and beta.

6. I determined the parameter bias (the average difference between the estimated parameter and its value used in generating the simulated subjective probabilities) for both alpha and beta.

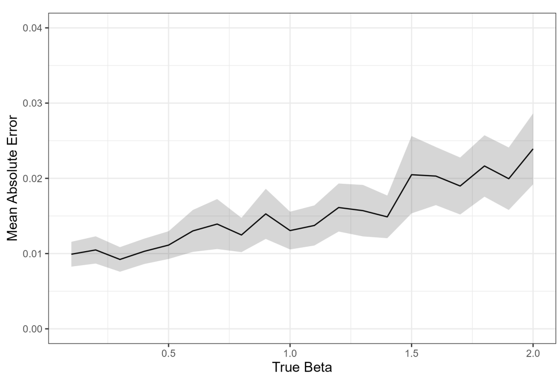
In my results, I focus on both the parameter mean absolute error and the parameter bias. In both cases, the results suggest good model recoverability. For instance, across parameter values, the average mean absolute error was 0.007 for the alpha parameter and 0.015 for the beta parameter. The average bias was even smaller: -0.002 for alpha and -0.005 for beta. In the following figure, I present these results disaggregated by each parameter value used in the subjective probability simulation. Specifically, plots a and b present the mean absolute error and the mean bias of the estimated alpha parameters for different true values of alpha. In plots c and d, I present the mean absolute error and the mean bias of the estimated beta parameters for different true values of beta.



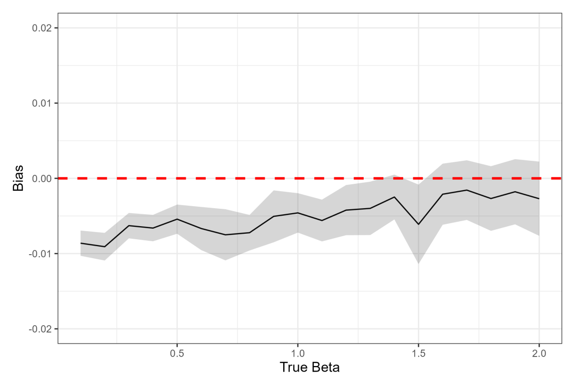
(a) Alpha MAE



(b) Alpha Bias



(c) Beta MAE



(d) Beta Bias

SM Note 7: Extended Simulations

In this supplemental note, I expand on the simulations presented in the main body of the manuscript by considering the impact of information frictions of varying intensities. Specifically, in this note, I consider every combination of four levels of information quantity frictions (where agents have access to information from 2, 4, 8, or all other agents in the group) and five levels of information quality frictions (where agents perceive the subjective probability assigned to an event by those in their network plus a normally distributed error term with a mean of zero and standard deviation of 0, 0.025, 0.05, 0.075, or 0.1 respectively). This yields a total of 20 information frictions specifications.

To conduct these additional simulations, I followed the same procedure I used in the main body of the paper. That is, the simulations were performed on groups of 16 agents located on a grid, with agent A11 being a stubborn agent. However, to streamline the computational process, I incorporated two key changes:

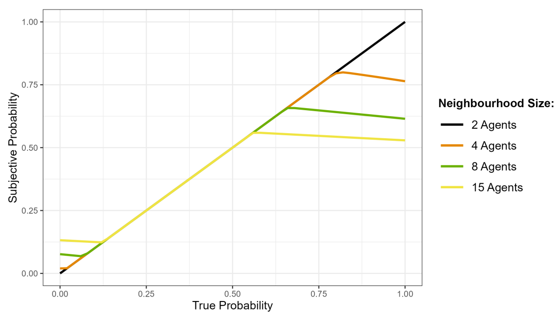
1. Instead of considering events with true probabilities ranging from 0 to 1 in increments of 0.01, I examined probabilities that ranged from 0 to 1 in 0.02 increments.

2. Instead of averaging results over 100 model repetitions, I did so over 50 repetitions.

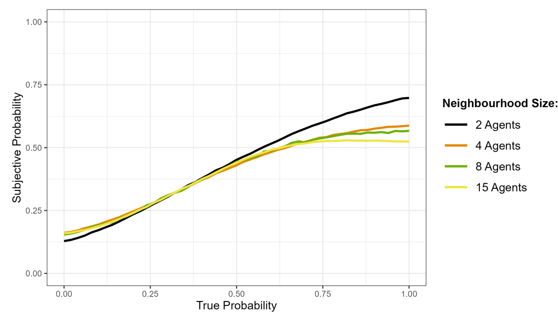
These departures are expected to have a very minor impact on the simulation results, while substantially lowering their computational costs. The rest of the simulation features were kept as in the simulations presented in the main body of the paper.

In the following page, I present the resulting patterns of subjective probabilities after 50,000 model iterations for each specification of information frictions considered. Specifically, each panel presents the resulting pattern of subjective probabilities under different degrees of information availability frictions and a given information quality friction (denoted by the standard deviation of the error term added to the agents' perceptions of the subjective probabilities of others). For instance, panel "b" presents the resulting patterns of risk perception when the agents perceive the subjective probabilities of others with an error terms that is normally distributed with mean 0 and a SD of 0.025. Panel "a" presents the resulting patterns of risk perception under no information quality frictions.

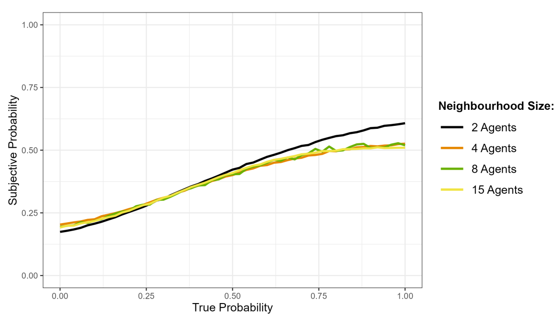
These results point to several important insights. First, these additional results go in line with the results presented in the main body of the paper. Specifically, across specifications, limits on the quality of the information that is socially shared leads to a more imprecise information transmission process. On the other hand, limits on the amount of information that is socially shared lead to a more precise information transmission process. Second, information quantity frictions have a greater impact on the resulting subjective probabilities of the group in the absence of information quality frictions. Even a mild error in perceiving others' subjective probabilities has a limiting effect on the impact of information quantity frictions on the resulting pattern of subjective probabilities. Third, when information quality frictions are large (i.e., when agents perceive the subjective probability assigned to an event by those in their network plus a normally distributed error term with a mean of zero and standard deviation of 0.1), introducing information availability frictions has a minor impact on the resulting pattern of subjective probabilities.



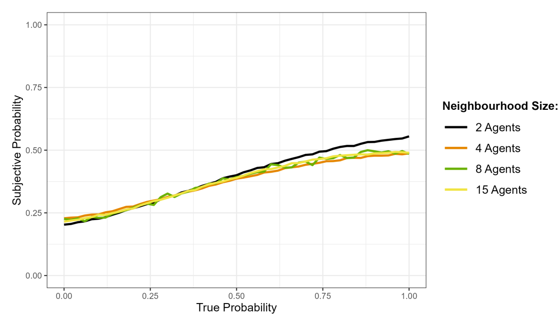
(a) SD = 0



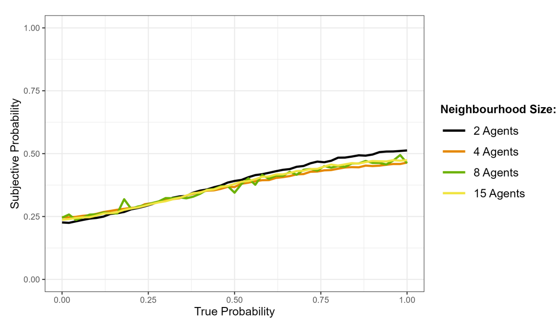
(b) SD = 0.025



(c) SD = 0.05



(d) SD = 0.075



(e) SD = 0.1

References

Abdellaoui, M., Baillon, A., Placido, L., & Wakker, P. P. (2011). The rich domain of uncertainty: Source functions and their experimental implementation. *American Economic Review*, *101*(2), 695–723.

Acemoglu, D., Ozdaglar, A., & ParandehGheibi, A. (2010). Spread of (mis) information in social networks. *Games and Economic Behavior*, *70*(2), 194–227.

Baillon, A., Huang, Z., Selim, A., & Wakker, P. P. (2018). Measuring ambiguity attitudes for all (natural) events. *Econometrica*, *86*(5), 1839–1858.

Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics*, *107*(3), 797–817.

Banerjee, A. V., & Fudenberg, D. (2004). Word-of-mouth learning. *Games and Economic Behavior*, *46*(1), 1–22.

Barberis, N. C. (2013). Thirty years of prospect theory in economics: A review and assessment. *Journal of Economic Perspectives*, *27*(1), 173–196.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, *100*(5), 992–1026.

Bordalo, P., Gennaioli, N., & Shleifer, A. (2012). Salience theory of choice under risk. *The Quarterly Journal of Economics*, *127*(3), 1243–1285.

Borsboom, D., van der Maas, H. L., Dalege, J., Kievit, R. A., & Haig, B. D. (2021). Theory construction methodology: A practical framework for building theories in psychology. *Perspectives on Psychological Science*, *16*(4), 756–766.

Brown, G. D., Lewandowsky, S., & Huang, Z. (2022). Social sampling and expressed attitudes: Authenticity preference and social extremeness aversion lead to social norm effects and polarization. *Psychological Review*, *129*(1), 18.

Busby, J. S., Onggo, B. S., & Liu, Y. (2016). Agent-based computational modelling of social risk responses. *European Journal of Operational Research*, *251*(3), 1029–1042.

Charness, G., Gneezy, U., & Imas, A. (2013). Experimental methods: Eliciting risk preferences. *Journal of economic behavior & organization*, *87*, 43–51.

Clement, J., & Puranam, P. (2018). Searching for structure: Formal organization design as a guide to network evolution. *Management Science*, *64*(8), 3879–3895.

Crane, R., & Sornette, D. (2008). Robust dynamic classes revealed by measuring the response function of a social system. *Proceedings of the National Academy of Sciences*, *105*(41), 15649–15653.

Deck, C., & Jahedi, S. (2015). The effect of cognitive load on economic decision making: A survey and new experiments. *European Economic Review*, *78*, 97–119.

Dimmock, S. G., Kouwenberg, R., & Wakker, P. P. (2016). Ambiguity attitudes in a large representative sample. *Management Science*, *62*(5), 1363–1380.

Einhorn, H. J., & Hogarth, R. M. (1985). Ambiguity and uncertainty in probabilistic inference. *Psychological Review*, *92*(4), 433.

Einhorn, H. J., & Hogarth, R. M. (1986). Decision making under ambiguity. *Journal of Business*, S225–S250.

Enke, B., & Graeber, T. (2019). *Cognitive uncertainty* (tech. rep.). National Bureau of Economic Research.

Eyster, E., & Rabin, M. (2010). Naive herding in rich-information settings. *American Economic Journal: Microeconomics*, *2*(4), 221–43.

Fan, K., & Pedrycz, W. (2016). Opinion evolution influenced by informed agents. *Physica A: Statistical Mechanics and Its Applications*, *462*, 431–441.

Fried, E. I. (2020). Lack of theory building and testing impedes progress in the factor and network literature. *Psychological Inquiry*, *31*(4), 271–288.

Ghaderi, J., & Srikant, R. (2014). Opinion dynamics in social networks with stubborn agents: Equilibrium and convergence rate. *Automatica*, *50*(12), 3209–3215.

Granovetter, M. (1978). Threshold models of collective behavior. *American journal of sociology*, *83*(6), 1420–1443.

Gray, K., Rand, D. G., Ert, E., Lewis, K., Hershman, S., & Norton, M. I. (2014). The emergence of "us and them" in 80 lines of code: Modeling group genesis in homogeneous populations. *Psychological Science*, *25*(4), 982–990.

Gross, J., & De Dreu, C. K. (2019). The rise and fall of cooperation through reputation and group polarization. *Nature Communications*, *10*(1), 1–10.

Haer, T., Botzen, W. W., de Moel, H., & Aerts, J. C. (2017). Integrating household risk mitigation behavior in flood risk analysis: An agent-based model approach. *Risk Analysis*, *37*(10), 1977–1992.

Hakes, J., & Viscusi, W. K. (1997). Mortality risk perceptions: A bayesian reassessment. *Journal of Risk and Uncertainty*, *15*, 135–150.

Henkel, L. (2022). *Experimental evidence on the relationship between perceived ambiguity and likelihood insensitivity* (tech. rep.). ECONtribute Discussion Paper.

Hogarth, R. M., & Einhorn, H. J. (1990). Venture theory: A model of decision weights. *Management Science*, *36*(7), 780–803.

Hogarth, R. M., & Kunreuther, H. (1985). Ambiguity and insurance decisions. *The American Economic Review*, *75*(2), 386–390.

Hogarth, R. M., & Kunreuther, H. (1989). Risk, ambiguity, and insurance. *Journal of Risk and Uncertainty*, *2*(1), 5–35.

Holzmeister, F., Huber, J., Kirchler, M., Lindner, F., Weitzel, U., & Zeisberger, S. (2020). What drives risk perception? a global survey with financial professionals and laypeople. *Management Science*, *66*(9), 3977–4002.

Jaspersen, J. G., & Ragin, M. A. (2021). A model of anchoring and adjustment for decision-making under risk. *Available at SSRN 3845633*.

Johnson, J. G., & Busemeyer, J. R. (2016). A computational model of the attention process in risky choice. *Decision*, *3*(4), 254.

Kahneman, D., Slovic, S. P., Slovic, P., & Tversky, A. (1982). *Judgment under uncertainty: Heuristics and biases*. Cambridge university press.

Kandiah, V., Binder, A. R., & Berglund, E. Z. (2017). An empirical agent-based model to simulate the adoption of water reuse using the social amplification of risk framework. *Risk Analysis*, *37*(10), 2005–2022.

Kasperson, R. E., Renn, O., Slovic, P., Brown, H. S., Emel, J., Goble, R., Kasperson, J. X., & Ratick, S. (1988). The social amplification of risk: A conceptual framework. *Risk Analysis*, *8*(2), 177–187.

Kasperson, R. E., Webler, T., Ram, B., & Sutton, J. (2022). The social amplification of risk framework: New perspectives.

Kempe, D., Kleinberg, J., & Tardos, É. (2003). Maximizing the spread of influence through a social network. *Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining*, 137–146.

Kim, H., Schroeder, A., & Pennington-Gray, L. (2016). Does culture influence risk perceptions? *Tourism Review International*, *20*(1), 11–28.

Li, Z., Müller, J., Wakker, P. P., & Wang, T. V. (2018). The rich domain of ambiguity explored. *Management Science*, *64*(7), 3227–3240.

Mason, W. A., Conrey, F. R., & Smith, E. R. (2007). Situating social influence processes: Dynamic, multidirectional flows of influence within social networks. *Personality and Social Psychology Review*, *11*(3), 279–300.

Mestdagh, M., Pe, M., Pestman, W., Verdonck, S., Kuppens, P., & Tuerlinckx, F. (2018). Sidelining the mean: The relative variability index as a generic mean-corrected variability measure for bounded variables. *Psychological Methods*, *23*(4), 690.

Moussaıd, M. (2013). Opinion formation and the collective dynamics of risk perception. *PLoS One*, *8*(12), e84592.

Raveendran, M., Puranam, P., & Warglien, M. (2022). Division of labor through self-selection. *Organization Science*, *33*(2), 810–830.

Robinaugh, D. J., Haslbeck, J. M., Ryan, O., Fried, E. I., & Waldorp, L. J. (2021). Invisible hands and fine calipers: A call to use formal theory as a toolkit for theory construction. *Perspectives on Psychological Science*, *16*(4), 725–743.

Scherer, C. W., & Cho, H. (2003). A social network contagion theory of risk perception. *Risk Analysis*, *23*(2), 261–267.

Siegrist, M., & Árvai, J. (2020). Risk perception: Reflections on 40 years of research. *Risk Analysis*, *40*(S1), 2191–2206.

Siggelkow, N., & Rivkin, J. W. (2005). Speed and search: Designing organizations for turbulence and complexity. *Organization Science*, *16*(2), 101–122.

Slovic, P. (2016). *The perception of risk*. Routledge.

Slovic, P., Fischhoff, B., & Lichtenstein, S. (1980). *Facts and fears: Understanding perceived risk*. Springer.

Slovic, P., & Peters, E. (2006). Risk perception and affect. *Current directions in psychological science*, *15*(6), 322–325.

Smith, V. K., & Johnson, F. R. (1988). How do risk perceptions respond to information? the case of radon. *The Review of Economics and Statistics*, 1–8.

Smith, V. K., & Michaels, R. G. (1987). How did households interpret chernobyl?: A bayesian analysis of risk perceptions. *Economics Letters*, *23*(4), 359–364.

Tompkins, M. K., Bjälkebring, P., & Peters, E. (2018). Emotional aspects of risk perceptions. *Psychological perspectives on risk and risk analysis: theory, models, and applications*, 109–130.

Trautmann, S. T., & Van De Kuilen, G. (2015). Ambiguity attitudes. *The Wiley Blackwell handbook of judgment and decision making*, *2*, 89–116.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *Science*, *185*(4157), 1124–1131.

Viscusi, W. K. (1985). Are individuals bayesian decision makers? *The American Economic Review*, *75*(2), 381–385.

Viscusi, W. K., & O'Connor, C. J. (1984). Adaptive responses to chemical labeling: Are workers bayesian decision makers? *The American Economic Review*, *74*(5), 942–956.

Watts, D. J. (2002). A simple model of global cascades on random networks. *Proceedings of the National Academy of Sciences*, *99*(9), 5766–5771.

Watts, D. J. (2004). The" new" science of networks. *Annual Review of Sociology*, 243–270.

Wu, F., & Huberman, B. A. (2007). Novelty and collective attention. *Proceedings of the National Academy of Sciences*, *104*(45), 17599–17601.

Yildiz, E., Ozdaglar, A., Acemoglu, D., Saberi, A., & Scaglione, A. (2013). Binary opinion dynamics with stubborn agents. *ACM Transactions on Economics and Computation (TEAC)*, *1*(4), 1–30.