Lancaster University
Management School

Economics Working Paper Series

2023/011

Testing Models of Complexity Aversion

Konstantinos Georgalos and Nathan Nabil

The Department of Economics
Lancaster University Management School
Lancaster LA1 4YX
UK

Testing Models of Complexity Aversion

Konstantinos Georgalos* Nathan Nabil†

October 31, 2023

Abstract

In this paper we aim to investigate how the complexity of a decision-task may change an agents strategic behaviour as a result of increased cognitive fatigue. In this framework, complexity is defined as a function of the number of outcomes in a lottery. Using Bayesian inference techniques, we quantitatively specify and estimate adaptive toolbox models of cognition, which we rigorously test against popular expectation based models; modified to account for complexity aversion. We find that for the majority of the subjects, a toolbox model performs best both in-sample, and with regards to its predictive capacity out-of-sample, suggesting that individuals result to heuristics when the complexity of a task overwhelms their cognitive load.

Keywords: Complexity aversion · Toolbox models · Heuristics · Risky choice · Bayesian modelling

JEL codes: C91 · D81 · D91

*Department of Economics, Lancaster University Management School, LA1 4YX, Lancaster, U.K.,✉: k.georgalos@lancaster.ac.uk, ORCID: 0000-0002-2655-4226

†Department of Economics, Lancaster University Management School, LA1 4YX, Lancaster, U.K.
✉ n.nabil@lancaster.ac.uk
We are grateful to Peter Moffatt, Stefania Sitzia and Daniel Zizzo for making their data available, and to Daniel Zizzo for providing useful comments. The support of The High End Computing (HEC) facility at Lancaster University is gratefully recognised.

1 Intro

In the recent years, the economic environment has witnessed a noticeable surge in complexity, driven by a confluence of interconnected factors. Technological advancements and globalization have expanded choices and convenience, while at the same time they have introduced overwhelming options that demand more of the consumers' attention and time. Mortgages, financial products, investment decisions and cryptocurrencies, all come with a plethora of options and features, that can exacerbate consumer decision-making, contributing to their increased cognitive fatigue.

In the field of choice under risk, complexity is represented by the number of payoff outcomes in a particular lottery. Early research on this topic has found that *complexity aversion* is a common attribute in subjects' behaviour, that is they reveal a strong preference for simple lotteries over complex ones (lotteries with higher number of outcomes). Huck and Weizsäcker (1999) and Sonsino et al. (2002) were among the first to provide evidence that individuals discriminate heavily against complicated lotteries, such that even when the expected value was fixed, they still prefer the lotteries with fewer outcomes even when these lotteries have a higher variance. Moffatt et al. (2015) estimate the distribution of attitudes towards complexity, finding that 50% are complexity-averse, 33% complexity-neutral, and only 17% complexity-loving. They also find that this rate of responsiveness to complexity reduces with experience to the extend that the average subject becomes almost complexity neutral by the end of the experiment. This convergence to complexity neutrality does not necessarily mean that the subjects no longer have a distaste for complex tasks, as it could be that they merely adopted a different strategy to make their decision, one which meant the complexity of the task was no longer hindering their decision process (i.e. heuristics).

From a theoretical modelling point of view, various expectation based utility models (e.g. mean-variance, Expected Utility, Cumulative Prospect Theory) have been modified to capture complexity aversion. Moffatt et al. (2015) test versions of the mean-variance model, and expected utility, while Fudenberg and Puri (2022), propose a model that combines the standard cumulative prospect theory (CPT) model with a complexity cost. This model captured preferences for lotteries with smaller number of outcomes and show that both probability weighting and complexity costs have an important role to play in predicting these risky alternatives. Diecidue et al. (2015) find that their results are consistent with prospect theory, but can also be explained by a population with heterogeneous aspiration levels. On the other hand, Bernheim and Sprenger (2020) find that PT and CPT fail rigorous tests that they design, and conclude that there is a possibility the observed behaviour reflects a combination of standard CPT and a form of complexity aversion linked to heuristics. While Georgalos and Nabil (2023) show that the descriptive capacity of CPT is decreasing on the level of complexity in a dataset.

Previous research has also suggested that when decisions are more complex, individuals may avoid making a decision altogether, they might procrastinate, but more often than not they decide to stick with a default option or strategy (Iyengar and Lepper 2001; Thaler and Sunstein 2009). This lead a strand of the literature to associate the distaste for complexity with an increase in one's cognitive load and therefore, an increase in reliance on simplified strategies or heuristics (rules of thumb). Venkatraman et al. (2014) shows that when faced with multiple-outcome gambles involving probabilities of both gains and losses, people often use simple heuristics that maximise the overall probability of winning. Coricelli et al. (2018) find that subjects may employ both a simplifying strategy and a compensatory strategy, providing evidence in support of a multiple-strategy approach to decision making.(Oberholzer et al.; 2021) report evidence of complexity aversion, suggesting a tendency to avoid cognitive effort as a potential explanation. Zeisberger (2022) suggest that the more complex the decision problem, the more likely it is the decision-maker will apply heuristics. Further studies have also supported the idea that complexity induces the use of heuristics with a focus on gain and loss probabilities (Erev et al. 2010; Payne 2005).

While this literature hints towards the increased use of heuristics and simplification strategies as a response to the increased cognitive load, this topic has not been thoroughly investigated in the context of choice under complexity. This is a gap in the literature that we aspire to bridge. In this short paper, we aim to study the effects of complexity on decision making and whether the increased complexity, and therefore the increased cognitive fatigue, lead agents to resort to heuristic decision making (following simple rules of thumb) rather than using complicated expectation utility models that account for the level of complexity. The heuristics literature assumes that people are equipped with a repertoire of heuristics (strategies) and simplifying processes (rules of thumb) to solve the tasks they face in daily life. This idea has been theoretically modelled with the aid of a *cognitive toolbox*, from which people might adaptively choose their respective strategies. Payne et al. (1993) argued that the decision makers are equipped with a set of strategies and select among them when faced with a decision; an approach which was later extended in Gigerenzer (2002) who models decision making as probabilistic draws from a toolbox of heuristic rules. Scheibehenne et al. (2013) propose a model of strategy selection. More specifically, they suggest a framework on how to quantitatively specify a toolbox model of cognition, and how to rigorously test it using Bayesian inference techniques. Using data from an experiment designed to elicit preferences towards risk and complexity aversion, we implement the methodology suggested in Scheibehenne et al. (2013) to estimate cognitive toolbox models. We then test these models against popular expectation based utility models, modified to account for complexity aversion. We compare the models based on both their in-sample and out-of-sample (predictive) capacity. We find that for the majority of the subjects, a toolbox model of simple heuristics has better descriptive and prescriptive capacity than competing compensatory models.

2 Theoretical Framework

In this section we present the theoretical models designed to capture preferences towards complexity and risk. The subjective complexity of a choice task is generally characterised in the literature by the number of alternatives on the decision maker's choice set, or the number of payoff outcomes in a particular lottery (see among others Sonsino et al. 2002, Moffatt et al. 2015, Zilker et al. 2020, Fudenberg and Puri 2022). In our comparison, we include three expectation based utility models that have been developed or modified to account for this type of complexity, as well as a cognitive toolbox of heuristics. We include the two models tested in Moffatt et al. (2015), namely the *mean-variance* and the Viscusi (1989) *Prospective Reference Theory*, the *Simplicity Theory*, a recent Cumulative Prospect Theory specification to account for complexity, as proposed in Fudenberg and Puri (2022), and a toolbox model of simple heuristic rules, as proposed in Scheibehenne et al. (2013) and implemented in Stahl (2018).

2.1 Mean-Variance

This model assumes that the utility function of the decision maker takes into consideration the expected value of the lottery (mean), the variance (exposure to risk), and its complexity (measured by the number of outcomes). The utility function for an individual i is given by:

$$U(p,x) = \mu_{(p,x)} - \alpha_i \sigma^2_{(p,x)} - \gamma_i C_{(p,x)} \tag{1}$$

where $\mu_{(p,x)}$ is the expected value of the J-outcome lottery $\mathcal{L} = \{p_1, x_1; \cdots; p_J, x_J\}$ defined as:

$$\sum_{j=1}^{J} p_j x_j$$

$\sigma^2_{(p,x)}$ is the variance of the lottery defined as:

$$\sum_{j=1}^{J} p_j \left(x_j - \mu_{(p,x)}\right)^2$$

and $C_{(p,x)}$ is the measure of complexity of the lottery, operationalised as C=0 for a sure payoff, C=1 for a simple lottery, C=2 for a complex, and C=3 for a very complex lottery. The parameter α is closely related to the coefficient of absolute risk aversion, while γ represents the degree of complexity aversion when $\gamma > 0$.

2.2 Prospective Reference Theory

This model assumes that the decision makers do not take the stated probabilities at face value, but act as Bayesians, and view the prior probability of each outcome of the lottery $\mathcal{L}$ as $1/J$. The model follows the same specification as above but replaces the objective probabilities in the expected value formula with transformed ones of the form:

$$\tilde{p}_j = \frac{\delta\frac{1}{J} + p_j}{\delta + 1},\ j = 1, \ldots, J; J > 1 \tag{2}$$

The parameter δ defines the degree of probability distortion. When $\delta \to 0$ the transformed probabilities coincide with the objective ones. On the contrary, as $\delta \to \infty$, $\tilde{p}_j \to 1/J$.

2.3 Simplicity Theory

Simplicity theory, introduced in Fudenberg and Puri (2022), modifies the CPT model to account for complexity aversion by introducing a complexity cost that captures a preference for lotteries with fewer number of outcomes. The CPT-simplicity model is defined as:

$$U(p, x) = \sum_{j=1}^{J} u(x_j) \left[w\left(\sum_{k=1}^{j} p_k\right) - w\left(\sum_{k=1}^{j-1} p_k\right) \right] - C(|support(p)|)$$

where $C(x)$ is a three-parameter sigmoid cost function to account for complexity, specified as:

$$C(x) = \frac{\iota}{1 + e^{-\kappa(x-\rho)}} - \frac{\iota}{1 + e^{-\kappa(1-\rho)}}$$

with x being the number of outcomes of a lottery, ι the height of the function, ρ the midpoint of the rise, and κ the slope, with larger values of κ indicating a steeper slope[1]. The function satisfies the condition $C(1) = 0$, while $w(.)$ is the Tversky and Kahneman (1992) probability weighting function[2]:

$$w(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}} \tag{3}$$

Finally, a power (CRRA) utility function is assumed for the monetary payoffs transformation.

2.4 Cognitive Toolbox

Following Scheibehenne et al. (2013), a toolbox model can be represented by a set of different psychological processes or strategies f, and each strategy predicts a particular course of action, depending on the *ecology* of the decision environment. The outcome of this process can be modelled with the aid of a mixture proportion parameter β, which indicates the probability of choosing each strategy in the toolbox. For instance, for a particular toolbox TB consisting of J strategies, each strategy f_j will be selected with probability β_j, with $\sum_{j=1}^{J} \beta_j = 1$. For instance, a potential toolbox with 4 strategies would be defined as:

- Pick the lottery with the highest payoff (MAXIMIN) with probability β_1
- Avoid the lottery with the lowest payoff (MINIMAX) with probability β_2
- Pick the lottery with the highest most likely payoff (MOST LIKELY) with probability β_3
- Pick the lottery with the highest probability of the highest possible payoff (MOST PROBABLE) with probability $1 - \sum_{i=1}^{3} \beta_i$

This modelling specification allows for the underlying cognitive process of strategy selection to remain unspecified, given that the value of the parameter vector β will be estimated by the data, providing the empirical validation of the latent strategy mix. Given this mixture

[1]Sigmoid functions have been extensively used in the artificial neural networks literature.

[2]We also tried different specifications of the probability weighting function (both one and two-parameter functionals) with TK being the best performing specification.

specification, the compound probability of choosing lottery A can be specified based on the sum of the individual likelihoods of each f_j, weighted by the mixture probability β_j:

$$p(A|TB) = \sum_{j=1}^{J} [\beta_j \times P(A|f_j)] \quad (4)$$

where $P(A|f_j)$ is the individual predicted probability of each strategy. Since the most distinguishable feature of a toolbox model is its adaptive nature (each individual adopts their chosen strategies depending on the choice environment), we deviate from the standard practice of fixing a pre-determined set of strategies, same for all the subjects, and allow for heterogeneity between subjects, both in terms of size (how many strategies) and in terms of content (which strategies). The toolbox models we investigate can accommodate a variety of heuristics (out of a total of 10 heuristics extensively utilised in the literature[3]) and sizes (ranging from 2 to 5 strategies per toolbox[4]). We achieve so by estimating, for each subject, every potential toolbox of size up to 5, that is formed as a combination of a subset of the available 10 heuristics. This gives in total 627 toolbox models.

3 Data

We re-analyse the data from Moffatt et al. (2015). This dataset involves 80 subjects participating in a 2-phase experiment, where in each phase subjects faced 27 tasks in which they were asked to choose between two lotteries with the same expected value, but with differing degrees of complexity and risk (phase 2 consisted of the same 27 tasks presented in a different order). The experiment was incentivised using the random lottery incentive mechanism. The experimental design builds on Sonsino et al. (2002) and Sitzia and Zizzo (2011) single period tasks. The construction of the lotteries is based on the two tasks presented below. The first task involves

[3]We use the heuristics studied in Glöckner and Pachur (2012). In the Online Appendix there is the full list of heuristics along with a description of the choice they prescribe.

[4]Scheibehenne et al. (2013) discuss how including too many strategies can lead to the strategy sprawl problem.

the choice between a sure win (SW) and a simple 3-outcome lottery (S_3).

$$SW = \begin{cases} 107, & \text{with probability } 1 \end{cases} \quad S_3 = \begin{cases} 80, & \text{with probability } 0.40 \\ 100, & \text{with probability } 0.30 \\ 150, & \text{with probability } 0.30 \end{cases}$$

Using the S_3 lottery and following a particular procedure [5], it is then possible to generate a *complex* lottery, with nine outcomes, and a *very complex* lottery with 27 outcomes. The new lottery will be more complex, but at the same time *safer*, since it will be characterised by lower variance. On top of the SW lottery, they generated six simple, six complex and six very complex lotteries. Using three simple lotteries, they first generated three complex and three very complex lotteries. Then, using the so called *safe* version of the simple lotteries, which has decreased spread of the extreme outcomes and unchanged the middle outcome, they constructed three further complex and three very complex *safe* lotteries. The pairwise combinations between a subset of these lotteries, along with the SW lottery, gives the total of the 27 tasks (see Moffatt et al. 2015, Table 2a, pp. 152-153 for the full set of tasks). All lotteries have the same expected value which also contributes to the complexity of the task.

4 Econometric Analysis and Results

We estimate all the models using Hierarchical Bayesian econometric techniques, which allow for the simultaneous estimation of individual level parameters and the hyper-parameters of the group level distributions (see Balcombe and Fraser 2015; Ferecatu and Önçüler 2016; Baillon et al. 2020; Alam et al. 2022 and Gao et al. 2022 for some recent applications of Bayesian econometrics in risky choice). We compare models both *in-sample*, and *out-of-sample*. In particular, we first compare the models in-sample, based on the value of the Bayes Factor, using the data from phase 1 of the experiment. We then compare the models based on their out-of-

[5] To save on space, we briefly describe the process in the online appendix and we refer the interested reader to the original study (Moffatt et al. 2015, p.151).

sample predictive capacity (predicted log-likelihood) on the phase 2 tasks, using the estimates from phase 1. To capture stochasticity in choice, we model the error structure assuming a logit link function. The probability of choosing lottery A is given by:

$$p(A > B) = \frac{\exp(\phi U_A(p, x)}{\exp(\phi U_A(p, x) + \exp(\phi U_B(p, x)}$$

where $U(p, x)$ is the utility as defined in section 2, and ϕ an index of the sensitivity to differences in utility, to be estimated. The overall likelihood is a Bernoulli distribution that can be expressed as $P(D) = \prod p(A > B)^I \times (1 - p(A > B))^{(1-I)}$, where I is an indicator function, taking the value 1 when the subject chose A, otherwise 0. For the toolbox model, since the heuristics generate ordinal choice propensities (i.e. deterministic), we assume a *constant-error* choice rule to capture stochastic choice in the data, where the decision maker chooses with constant probability $1 - \varepsilon$, the option that the heuristic prescribes, and with probability ε she makes a mistake[6]. The overall likelihood for a given subject is therefore the product, across all the tasks, of the weighted sum of predicted probabilities across the number of strategies in a given toolbox.

Table 1 reports the results of the classification. The first column classifies subjects to models based on the value of the Bayes Factor, while the second column, according to the models' predictive capacity. In-sample, the toolbox model has the best performance for 56.3% of the subjects, followed by the mean variance (26.3%), the simplicity theory (16.3%) and only one subject is characterised by the Prospective Reference model. A similar pattern is also observed in our out-of-sample prediction exercise. The toolbox model is best for 60% of the subjects, followed by the mean variance (16.3%), the Prospective Theory model (13.8%) and the Simplicity Theory model (10%).

[6]This is the part $P(A|f_j)$ in Equation 4.

Model	In-sample	Out-of-sample
Toolbox	45	48
%	0.563	0.600
Mean-variance	21	13
%	0.263	0.163
Prospective Reference Theory	1	11
%	0.013	0.138
Simplicity Theory	13	8
%	0.163	0.100
TOTAL	80	80

Table 1: Number of subjects for which a model is classified as best, based on the in-sample fit (Bayes Factor) and the out-of-sample fit (predicted log-likelihood).

Given the performance of the toolbox model, we next focus on the size and the content of each toolbox. Figures 1 and 2, illustrate the distribution of the different sized toolboxes, both in and out-of-sample. In both cases, the majority of the subjects (who is classified as toolbox decision makers) uses 4 or 5 heuristics, while very few use only 2. This size is in line with previous results in the literature (see Makridakis and Winkler 1983; Ashton and Ashton 1985; He et al. 2022). There seems to be a slight drop in the size of toolboxes, out-of-sample, which could be the effect of learning and increased familiarity with the task.

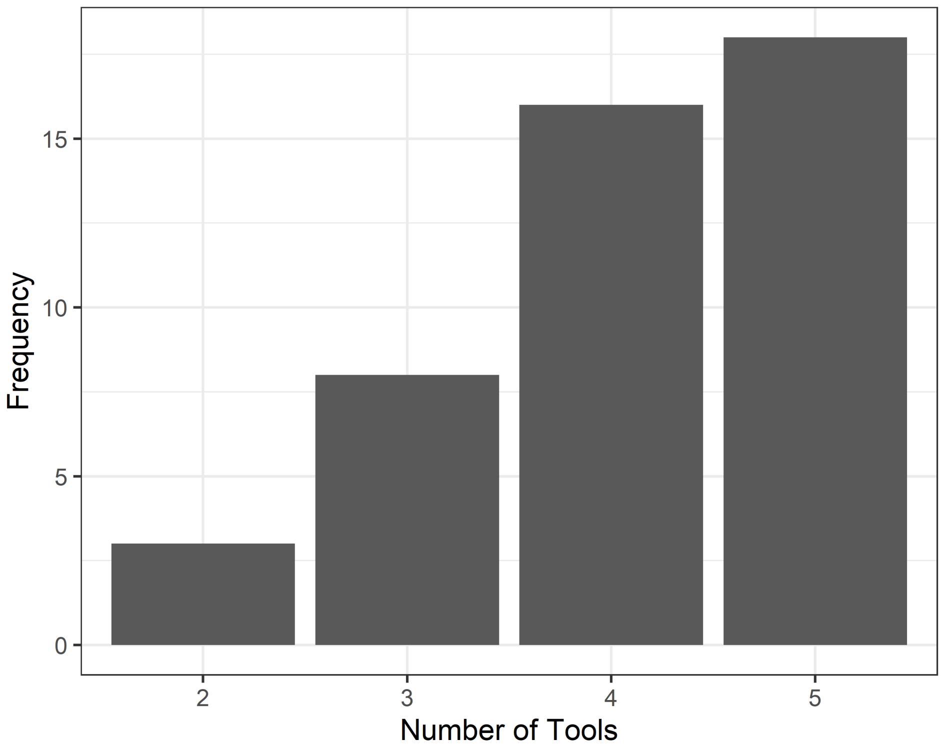

Figure 1: Frequency of toolbox sizes (in-sample).

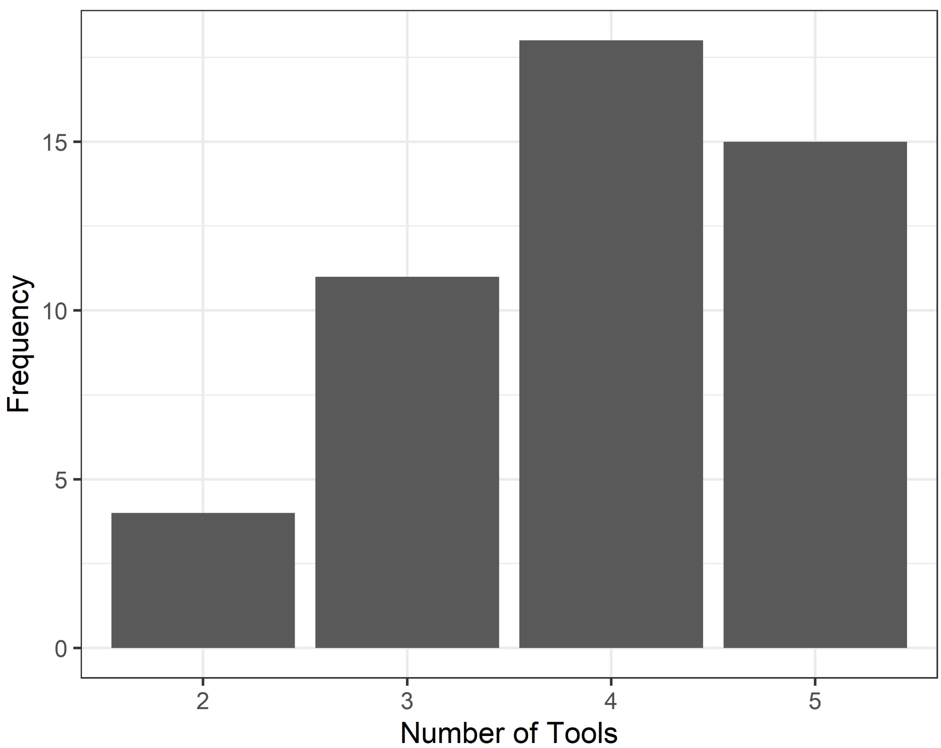

Figure 2: Frequency of toolbox sizes (out-of-sample).

Regarding the content of these toolboxes, Figures 3 and 4 illustrate the distribution of heuristics across all toolboxes, in and out-of-sample, respectively. Three heuristics outperformed all others, both in and out-of-sample as they were present in the majority of the toolboxes, namely, the Minimax (MINI), the Least Likely (LL) and the Equal Weight (EW). Similarly, the three worst performing heuristics, both in and out-of-sample were the Maximax (MAXI), the Equiprobable (EQUI) and the Most Likely (ML). Given the nature of these heuristics, it is easy to infer that subjects tend to resort to strategies that they will protect them from the worst case scenario (i.e. worst outcome), while avoid strategies that would expose them to higher levels of complexity. When we compare in and out-of-sample differences, there are two points worth mentioning: (1) we find strong evidence in favour of the Priority Heuristic (PRIO), in-sample, a heuristic that has received much attention in the literature because of its capacity to explain risky choice, and (2) the performance of PRIO falls massively in the out-of-sample prediction, which can be seen as an indicator a change in the strategy set that subjects adopt to tackle similar tasks. The PRIO is a lexicographic strategy that requires several rounds of reason comparing payoffs and probabilities and is therefore more cognitively demanding compared to simpler heuristics. This may be a potential explanation of the drop of complexity averse and seeking subjects that Moffatt et al. (2015) find in the phase 2 data.

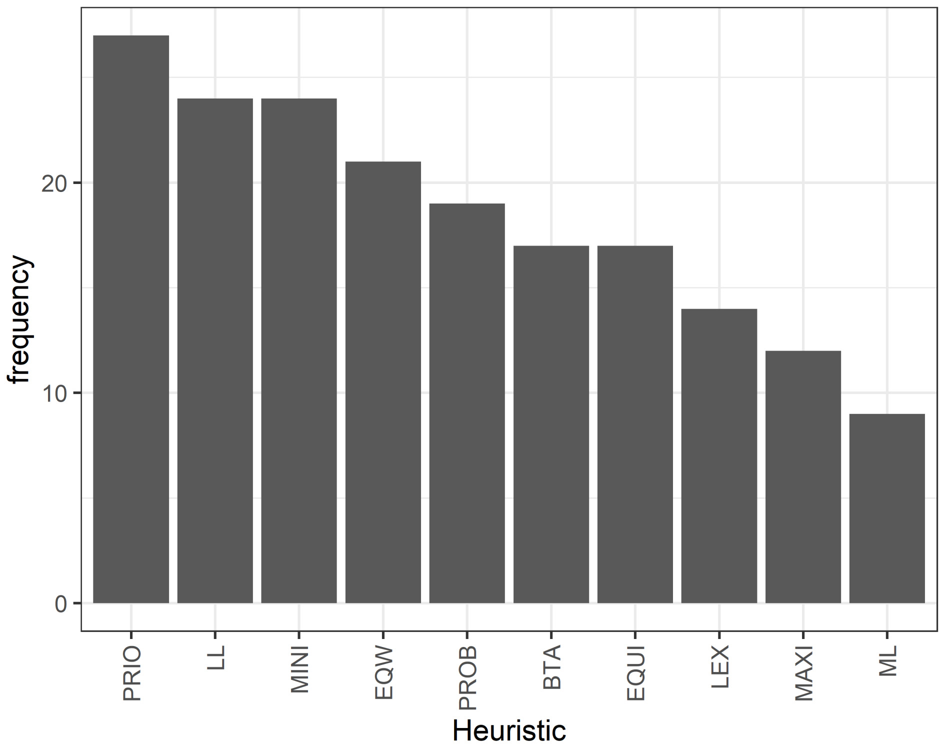

Figure 3: Frequency of heuristics (in-sample).

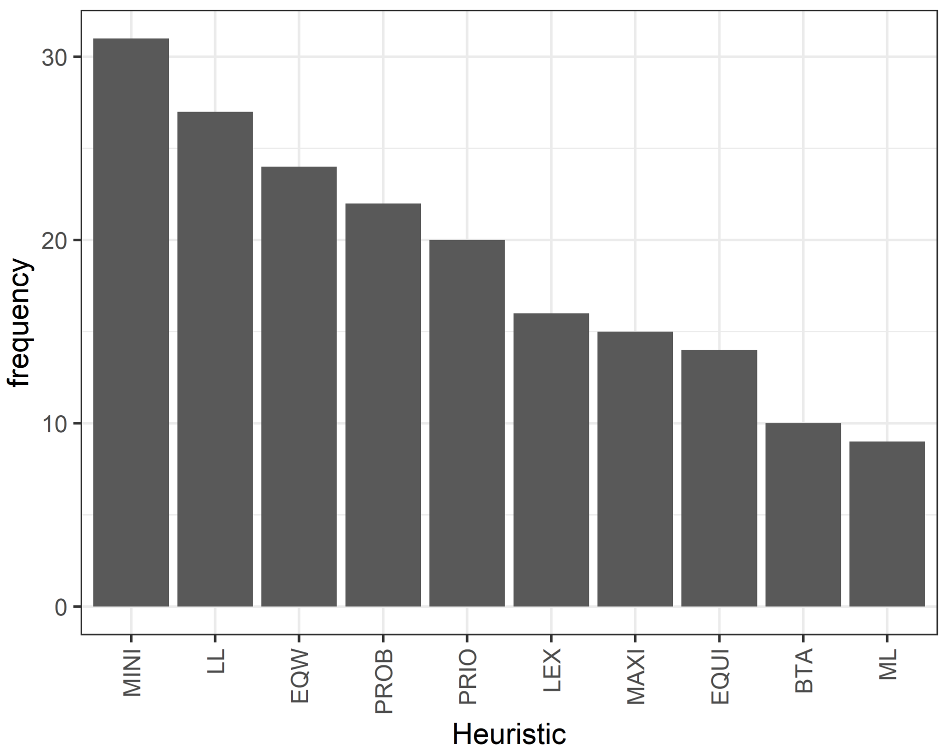

Figure 4: Frequency of heuristics (out-of-sample).

5 Conclusion

Our analysis highlights the importance of accounting for complexity when deciding on which explanatory model to adopt to describe individual behaviour. We have shown that with overly complex tasks comes increased cognitive fatigue in decision-making; a characteristic which heightens one's reliance on simple rules of thumb to make decisions. This results in an adaptive toolbox of heuristics outperforming other expectation based models of decision-making, even when complexity aversion is captured within these competing parametric models. We provide a means of efficiently estimating structural models of decision-making, including a toolbox model, in-sample via the use of Bayesian Hierarchical modelling, and illustrate the robustness of these results in their alignment with our out-of-sample prediction results.

Ironically, analysing strategic processes and preferences in the face of increased complexity is a complex matter in itself, and it is easy to neglect vital attributes of complexity. Whilst most studies use the number of alternatives in a choice set as the key metric, we would urge future research to consider the works of Diecidue et al. (2015), Huck and Weizsäcker (1999) and Georgalos and Nabil (2023) who discuss how the formatting of probabilities and outcomes, the distribution moments (e.g. variance and mean) and other factors may well fall into the complexity function. The latter design a metric as a benchmark to determine a data sets complexity levels.

Finally we would urge future studies to expand decision-tasks beyond binary lotteries, as research has suggested the impact of complexity on risk taking is largely dependent on the decision format (Oberholzer et al.; 2021). Before we jump to conclusions on complexity's effect on risky decision-making, we must ensure that numerous tasks of varying contexts and characteristics are examined, as it may be that the nature of certain tasks lead people to specific solutions.

References

Alam, J., Georgalos, K. and Rolls, H. (2022). Risk Preferences, Gender Effects and Bayesian Econometrics, *Journal of Economic Behavior & Organization* **202**: 168–183.

Ashton, A. and Ashton, R. (1985). Aggregating Subjective Forecasts: Some Empirical Results, *Management Science* **31**(12): 1499–1508.

Baillon, A., Bleichrodt, H. and Spinu, V. (2020). Searching for the Reference Point, *Management Science* **66**(1): 93–112.

Balcombe, K. and Fraser, I. (2015). Parametric Preference Functionals under Risk in the Gain Domain: A Bayesian Analysis, *Journal of Risk and Uncertainty* **50**(2): 161–187.

Bernheim, B. D. and Sprenger, C. (2020). On the empirical validity of cumulative prospect theory: Experimental evidence of rank-independent probability weighting, *Econometrica* **88**(4): 1363–1409.

Brandstätter, E., Gigerenzer, G. and Hertwig, R. (2006). The Priority Heuristic: Making Choices without Trade-Offs, *Psychological Review* **113**: 409–432.

Coricelli, G., Diecidue, E. and Zaffuto, F. D. (2018). Evidence for multiple strategies in choice under risk, *Journal of Risk and Uncertainty* **56**(3): 193–210.

Diecidue, E., Levy, M. and van de Ven, J. (2015). No aspiration to win? an experimental test of the aspiration level model, *Journal of Risk and Uncertainty* **51**: 245–266.

Erev, I., Ert, E., Roth, A. E., Haruvy, E., Herzog, S. M., Hau, R., Hertwig, R., Stewart, T., West, R. and Lebiere, C. (2010). A choice prediction competition: Choices from experience and from description, *Journal of Behavioral Decision Making* **23**(1): 15–47.

Ferecatu, A. and Önçüler, A. (2016). Heterogeneous Risk and Time Preferences, *Journal of Risk and Uncertainty* **53**(1): 1–28.

Fudenberg, D. and Puri, I. (2022). Simplicity and Probability Weighting in Choice under Risk, *American Economic Review Papers & Proceedings* **112**: 421–425.

Gao, X., Harrison, G. and Tchernis, R. (2022). Behavioral Welfare Economics and Risk Preferences: a Bayesian Approach, *Experimental Economics* .

Georgalos, K. and Nabil, N. (2023). Heuristics unveiled: A comparative analysis of toolbox models and prospect theory in risky choice. Lancaster University Management School, Economics Working Paper Series, 2023/010.

Gigerenzer, G. (2002). The Adaptive Toolbox, *in* G. Gigerenzer and R. Selten (eds), *Bounded Rationality: The Adpative Toolbox*, Cambridge, MA: MIT Press, pp. 37–50.

Glöckner, A. and Pachur, T. (2012). Cognitive models of risky choice: Parameter stability and predictive accuracy of prospect theory, *Cognition* (123): 21–32.

He, L., Analytis, P. and Bhatia, S. (2022). The Wisdom of Model Crowds, *Management Science* **68**(5): 3175–3973.

Huck, S. and Weizsäcker, G. (1999). Risk, complexity, and deviations from expected-value maximization: Results of a lottery choice experiment, *Journal of Economic Psychology* **20**: 699–715.

Iyengar, S. and Lepper, M. (2001). When choice is demotivating: Can one desire too much of a good thing?, *Journal of personality and social psychology* **79**: 995–1006.

Makridakis, S. and Winkler, R. (1983). Averages of Forecasts: Some Empirical Results, *Management Science* **29**(9): 987–996.

Moffatt, P., Sitzia, S. and Zizzo, D. (2015). Heterogeneity in Preferences Towards Complexity, *Journal of Risk and Uncertainty* **51**: 147–170.

Oberholzer, Y., Olschewski, S. and Scheibehenne, B. (2021). Complexity aversion in risky choices and valuations: Moderators and possible causes.

Payne, J., Bettman, J. and Johnson, E. (1993). *The Adaptive Decision Maker*, Cambridge University Press.

Payne, J. W. (2005). It is whether you win or lose: The importance of the overall probabilities of winning or losing in risky choice, *Journal of Risk and Uncertainty* **30**(1): 5–19.

Scheibehenne, B., Rieskamp, J. and Wagenmakers, E. (2013). Testing Adaptive Toolbox Models: A Bayesian Hierarchical Approach, *Phychological Review* **120**(1): 39–64.

Sitzia, S. and Zizzo, D. J. (2011). Does product complexity matter for competition in experimental retail markets?, *Theory and Decision* **70**(1): 65–82.

Sonsino, D., Benzion, U. and Mador, G. (2002). The Complexity Effects on Choice under Uncertainty, *The Economic Journal* **112**(482): 9.

Stahl, D. (2018). An Empirical Evaluation of the Toolbox Model of Lottery Choices, *The Review of Economics and Statistics* **100**(3): 528–534.

Thaler, R. H. and Sunstein, C. R. (2009). *Nudge: Improving Decisions About Health, Wealth, and Happiness*, Penguin Books.

Thorngate, W. (1980). Efficient decision heuristics, *Behavioral Science* **25**: 219–225.

Tversky, A. and Kahneman, D. (1992). Advances in Prospect Theory: Cumulative Representation of Uncertainty, *Journal of Risk and Uncertainty* **5**(4): 297–323.

Venkatraman, V., Payne, J. W. and Huettel, S. A. (2014). An overall probability of winning heuristic for complex risky decisions: Choice and eye fixation evidence, *Organizational Behavior and Human Decision Processes* **125**(2): 73–87.

Viscusi, W. K. (1989). Prospective reference theory: Toward an explanation of the paradoxes, *Journal of Risk and Uncertainty* **2**(3): 235–263.

Zeisberger, S. (2022). Do people care about loss probabilities?, *Journal of Risk and Uncertainty* **65**(2): 185–213.

Zilker, V., Hertwig, R. and Pachur, T. (2020). Age differences in risk attitude are shaped by option complexity, *Journal of Experimental Psychology: General* **149**(9): 1644–1683.

Appendix A Tasks

This Appendix briefly describes the procedure Moffatt et al. (2015) are using to generate the lotteries for their experiment. Consider the following lottery S_α:

$$S_3 = \begin{cases} 80, & \text{with probability } 0.40 \\ 100, & \text{with probability } 0.30 \\ 150, & \text{with probability } 0.30 \end{cases}$$

This simple lottery with 3 outcomes, can generate a complex lottery with 9 outcomes, and a very complex lottery with 9 outcomes. In vector form, this lottery can be written as $S_\alpha = (p, x) = \Big((p_1 p_2 p_3)', (x_1, x_2, x_3)'\Big)$. A complex lottery C_α can be generated from S_α using the formula:

$$C_\alpha = \left(vec(pp'); vec\left(\frac{1}{2}xi_3' + \frac{1}{2}i_3x'\right)\right)$$

where i_3 is a vector of size 3 consisting of ones and $vec(A)$ is the function that transforms a $n \times n$ matrix A into a $n^2 \times 1$ (column) vector consisting of the elements of A. This lottery is equivalent to playing S_α twice and using the arithmetic mean outcome from the two plays as the outcome.

Applying this to the above lottery, we get:

$$vec(p \times p') = \begin{bmatrix} 0.16 & 0.12 & 0.12 \\ 0.12 & 0.09 & 0.09 \\ 0.12 & 0.09 & 0.09 \end{bmatrix} = \begin{bmatrix} 0.16 & 0.12 & 0.12 & 0.12 & 0.09 & 0.09 & 0.12 & 0.09 & 0.09 \end{bmatrix}$$

and $vec(pp'$ generates a vector of size eleven with the element of the $p \times p'$ matrix. Then, for the payoffs:

$$vec\left(\frac{1}{2}xi_3' + \frac{1}{2}i_3x'\right) = \begin{bmatrix} 80 & 90 & 115 & 90 & 100 & 125 & 115 & 125 & 150 \end{bmatrix}$$

which gives the lottery

$$C_3 = \begin{cases} 80, & \text{with probability } 0.16 \\ 90, & \text{with probability } 0.24 \\ 100, & \text{with probability } 0.09 \\ 115, & \text{with probability } 0.24 \\ 125, & \text{with probability } 0.18 \\ 150, & \text{with probability } 0.09 \end{cases} \quad S_3 = \begin{cases} 80, & \text{with probability } 0.40 \\ 100, & \text{with probability } 0.30 \\ 150, & \text{with probability } 0.30 \end{cases}$$

Using a similar procedure, it is possible to create a very complex lottery with 27 outcomes. For the full set of tasks please see Moffatt et al. (2015, Table 2a, pp. 152-153).

Appendix B List of Heuristics

Table 2: Table of heuristics

	Heuristic	Description
1.	Priority Heuristic (PRIO)	Go through reasons in the order of: minimum gain, probability of minimum gain, and maximum gain. Stop examination if the minimum gains differs by 1/10 (or more) of the maximum gain; otherwise, stop examination if probabilities differ by 1/10 (or more) of the probability scale. Choose the gamble with the more attractive gain (probability).
2.	Equiprobable (EQUI)	Calculate the arithmetic mean of all outcomes for each gamble. Choose the gamble with the highest mean.
3.	Equal-weight (EQW)	Calculate the sum of all outcomes for each gamble. Choose the gamble with the highest sum.
4.	Better than average (BTA)	Calculate the grand average of all outcomes from all gambles. For each gamble, count the number of outcomes equal to or above the grand average. Then choose the gamble with the highest number of such outcomes.
5.	Probable (PROB)	Categorize probabilities as probable (i.e., $\geq 1/2$ for a two-outcome gamble, $\geq 1/3$ for a three-outcome gamble, etc.) or improbable. Cancel improbable outcomes. Then calculate the arithmetic mean of the probable outcomes for each gamble. Finally, choose the gamble with the highest mean.
6.	Minimax (MINI)	Choose the gamble with highest minimum outcome.
7.	Maximin (MAXI)	Choose the gamble with the highest outcome.
8.	Lexicographic (LEX)	Determine the most likely outcome of each gamble and choose the gamble with the better outcome. If both outcomes are equal, determine the second most likely outcome of each gamble, and choose the gamble with the better (second most likely) outcome. Proceed until a decision is reached.
9.	Least likely (LL)	Identify each gamble's worst outcome. Then choose the gamble with the lowest probability of the worst outcome.
10.	Most likely (ML)	Identify each gamble's most likely outcome. Then choose the gamble with the highest, most likely outcome.

Heuristics are from Thorngate (1980) and Payne et al. (1993), later used in Brandstätter et al. (2006) and Glöckner and Pachur (2012).