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# Description–experience gap under imperfect information

## Information continuum and aggressive cost estimating in capital projects



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### Abstract

**Purpose** – Capital project delivery, such as the delivery of transportation networks and industrial facilities, often suffers losses due to overly aggressive planning. Planners often are overly optimistic about the chance of success while underestimating risks. The purpose of this paper is to examine the hypothesis that these biases are from the difficulties most decision makers face when interpreting probabilistic information.

**Design/methodology/approach** – Three behavioral experiments were conducted to test the theoretical fitness of the paradigms proposed by the description–experience gap literature, namely, the sampling errors effect, the recency effect and statistical information format. College students were recruited to participate in a series of estimating tasks. And their estimating results were compared given different levels of information completeness.

**Findings** – It was found that the existing paradigms could predict risk decision making in the risk-averse estimating scenarios where test subjects were required to give a relatively conservative estimate, but they seemed to be less effective in predicting decisions in the risk-seeking estimating scenario, where test subjects were asked to give a relatively aggressive estimate.

**Originality/value** – Based on these findings, an integrative model is proposed to explain the observations pertaining to aggressive planning in capital projects. Two dimensions are deemed to be relevant: including risk-taking intentions, and an information uncertainty continuum that ranges from an implicit experience-based information representation to an explicit description-based information representation.

**Keywords** Decision support systems, Estimating, Construction planning

**Paper type** Research paper

## Introduction

Capital projects, such as roads, bridges, processing plants and power plants, are the infrastructure of the world's economy (City of Portland, 2016). The expenditure on capital projects is tremendous, with $22 trillion in projected investments by 2018 in emerging economies alone, *The Economist* calls it "the biggest investment boom in history" (*The Economist*, 2008). Despite the importance of capital projects to the economy, there is a demonstrated, systematic and chronic tendency for project planners to give unanimously aggressive cost estimates in the budgeting phase (Flyvbjerg, 2008; Treasury, 2003a, b; Love and Ahiaga-Dagbui, 2018). Estimating inaccuracy was found to be, on average,

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44.7 percent for rail, 33.8 percent for bridges and tunnels, and 20.4 percent for roads (Flyvbjerg, 2008). The aggressive budget and insufficient allocation of necessary resources have caused significant cost escalation and time extension of many high-profile capital projects (Flyvbjerg, 2008). This issue has not improved over the last century, or across different geographic regions (Flyvbjerg *et al.*, 2003). Despite all claims of improved forecasting models and better data, no improvements in the estimating accuracy of capital projects have been observed (Flyvbjerg, 2008; Treasury, 2003a, b).

Literature has identified two main reasons that why planners of capital projects make aggressive plans. The first relates to the strategic misrepresentation. Planners may deliberately and strategically underestimate costs to increase the likelihood of receiving approval and funding (Flyvbjerg *et al.*, 2005). Recently, Gil *et al.* have also investigated the strategic planning with a polycentric governance approach (Gil, 2017; Gil, N.A., 2016; Gil and Pinto, 2018, 2017). It was found that the challenge of agreeing on strategic choices with multiple stakeholders with conflicting goals to be a major contributor to the overruns (Gil *et al.*, 2017; Gil and Pinto, 2017; Gil *et al.*, 2015; Lundrigan and Gil, 2013). They further proposed a pluralistic setting where project outcomes were reportedly well aligned with strategic plans albeit scarce resources and longtime horizons (Gil, N., 2016; Gil and Baldwin, 2014). The second explanation, which is gaining more attention recently, pertains to a psychological inclination of most people to be overly optimistic about the outcome of planned actions (Flyvbjerg, 2008). This includes overestimating the likelihood of positive events and underestimating risk and loss (Flyvbjerg, 2008). This “delusional optimism,” as described by Daniel Kahneman *et al.*, stems from the way people choose between probabilistic alternatives that involve risk (Kahneman and Tversky, 1979; Lovallo and Kahneman, 2003).

According to prospect theory, the decision weights of prospects, i.e. outcomes associated with probabilities, are considered differently depending on whether the prospects have a high or low probability and the nature of the outcomes (Kahneman and Tversky, 1979). To be more specific: people tend to overreact to low probability events and underreact to high probability ones (Tversky and Kahneman, 1992). In other words, people appear to be risk-seeking when facing a situation from which there is something to be gained, while are more risk-averse when facing a situation from which there is something to be lost. Because its validity has been demonstrated by numerous behavioral experiments, prospect theory has been employed to explain the aggressiveness in capital project cost estimating (Ahiaga-Dagbui and Smith, 2014; Cantarelli *et al.*, 2013; Flyvbjerg, 2013). It is argued that the distorted utility function due to varying decision heuristics and reactions to probabilities has caused the observed bias in cost estimating (Ahiaga-Dagbui and Smith, 2014; Flyvbjerg, 2013).

However, this argument lacks sufficient external validity. First, prospect theory addresses risk decision making based on the given priori probabilities, or decision from descriptions (Hertwig and Erev, 2009). Yet in most business decision-making scenarios including capital project cost estimating, people rarely have the access to explicit descriptions of probability distributions. Instead, they have to rely on previous experiences to make decisions, or decision from experiences (Hertwig *et al.*, 2004). This is especially the case in the planning of capital projects. Due to the complexity and variety of capital projects, most planners only gain limited knowledge from the sparse data. Therefore, the decision making is often an inductive reasoning process, i.e. building knowledge of the probability based on learned experience and making choices based on the perceived statistical probability of events (Schwanen and Ettema, 2009). Accumulating evidence indicates that decision from experiences and decision from descriptions tend to show opposite forms of responding, referred to as the description–experience gap (Camilleri and Newell, 2013; Hau *et al.*, 2008; Hertwig and Erev, 2009).

This study aims to investigate the aggressiveness in capital project cost estimating from the perspective of individuals' imperfect ability of processing uncertainty of information. Specifically, this study aims to investigate how the different levels of explicit information presentation affects and changes the bias of estimators in cost estimating. Three human-subject experiments will be introduced to explore scenarios ranging from the most implicit to the most explicit information presentations.

## Literature review

### *Aggressive cost estimating in capital projects*

A number of explanations exist for the observed aggressiveness in capital project cost estimating. The most common theory attributes aggressiveness to political and organizational pressures, such as competition for scarce funds or jockeying for position, and to the lack of incentive alignment (Flyvbjerg *et al.*, 2013; Flyvbjerg, 2017). Researchers have also examined the impact of technical difficulties in cost estimating due to the long planning horizon and complex interfaces of capital projects (Flyvbjerg *et al.*, 2013; Jennings, 2012). Another line of investigation has identified various decision making issues that may contribute to over-aggressiveness. A popular explanation, identified by Daniel Kahneman, pertains to people's inclination to overestimate benefits and underestimate costs (Kahneman and Tversky, 1979; Lovallo and Kahneman, 2003). Indeed, this explanation has become so popular that the UK Government and the American Planning Association (APA) recommended adopting a technique proposed by Kahneman *et al.* to combat this effect (American Planning Association, 2005). The technique, known as reference class forecasting (RCF), involves having decision makers identify comparable projects and base their judgments of the likely costs, benefits, obstacles, etc., on those actually encountered in the reference projects (Lovallo and Kahneman, 2003).

Based on previous work, we hypothesize that biases stem from the difficulty most decision makers face when interpreting probabilistic information (Ghazal *et al.*, 2014). When making judgments and decisions under uncertainty, people often rely on simplified heuristics (Hogarth and Karelaia, 2007). Although heuristics are often effective (Hogarth and Karelaia, 2007), they can also introduce biases into the process at various levels of analysis. To better identify what these biases may be and how they occur, we examined the research in the prospect theory and the description–experience gap.

### *From prospect theory to description–experience gap*

Kahneman and Tversky (1979) proposed the prospect theory to explain why a person would switch risk attitudes in decision making. It was contemplated and later confirmed by numerous behavioral experiments, that there is a tendency for people to overestimate extreme events (Lovallo and Kahneman, 2003). The natural consequence is that people appear to be risk-seeking when facing a situation from which there is something to be gained (i.e. evaluating options related to getting something), while are more risk-averse when facing a situation from which there is something to be lost (i.e. evaluating options related to losing something) (Barberis *et al.*, 2016). The prospect theory provides a theoretical framework to predict risk decision making in a variety of uncertain or certain prospects. The distortion predicted by the prospect theory is called the reflection effect (Duke *et al.*, 2017).

However, recently, increasing evidence has shown that human risk decisions can behave in a manner that is opposite to what is predicted by prospect theory: in a series of experiments, it was discovered that subjects could underweight, instead of overweight, extreme events, if they were provided with incomplete information (Camilleri and Newell, 2013; Hau *et al.*, 2008; Ludvig and Spetch, 2011). This discovery was named the reverse reflection effect to highlight the deviation from the reflection effect (Camilleri and Newell, 2013). It was believed that the most straightforward reason is whether a person is making decisions from descriptions or from experience. As a result, Camilleri and Newell (2013) coined the term "description–experience gap" to describe the discrepancy between the two theories.

The discrepancy can partially be attributed to the uncertainty in decision making. The level of uncertainty is related to the amount of information and knowledge to describe it. Knight (2012) distinguished between uncertainty situations where people can use priori probabilities or statistical probabilities in decision making. The former is usually obtained from established knowledge and definitions, such as calculations based on physics, while the latter relies on an observation that is dynamically changing and more implicit (Knight, 2012). The prospect theory shows a strong predictability in situations where decisions are made from the definitive description of priori probabilities, but is less effective in situations where decisions are made from implicit and learned statistical probabilities (Hau *et al.*, 2010).

*Causes of description–experience gap*

Literature has identified a series of possible causes contributing to the description–experience gap. The most commonly cited one is the sampling errors effect (Hau *et al.*, 2010, 2008). Due to the limited accessibility to data, people often need to rely on small samples to make decisions (Hau *et al.*, 2010). Statistically, it is more difficult to understand rare events with a small sample size, and hence they tend to be underestimated. Although some scholars claim that the sampling errors effect could be simply reduced to a statistical phenomenon instead of a psychological process (Hau *et al.*, 2008; Rakow *et al.*, 2008), recent evidence indicates that there remains an unexplained gap in experiments even if population-sample error has been taken into account (Bodemer *et al.*, 2014; Hoffrage *et al.*, 2000). It suggests that the sampling errors effect involves certain cognitive processes that are not yet adequately explored.

The second explanation relates to the recency effect, i.e. a phenomenon that observations made late in a sequence received more weight than they deserve (Plonsky *et al.*, 2015). According to the cognitive load theory, human cognition has a finite information processing capacity (Lachman *et al.*, 2015). The recency effect is the result of the apparent gap between the enormous information processing needs in decision making and the limited processing capacity. If the thesis of the recency effect holds, it could be reduced to a process similar to the sampling errors effect because the amount of information that can be used in the decision making is still limited, in spite of the increased accessibility to data.

Finally, the description–experience gap may also be mediated by different ways of representing statistical information (Camilleri and Newell, 2013; Hertwig and Erev, 2009). Description-based decisions are usually associated with explicitly demonstrated information, while experience-based decisions involve a Bayesian reasoning (Hertwig and Erev, 2009). Due to certain unknown cognitive and neurobiological processes, people seem to have better ability in processing natural frequency information than probability information (Bodemer *et al.*, 2014; Hoffrage *et al.*, 2000). It is possible that the variety of information formats used in description-based decisions and experience-based decisions contributes to the gap.

In the remainder of this paper, we will introduce three experiments intended to test the theoretical fitness of the paradigms in explaining aggressive estimating in a capital project. The central question is: Will different levels of explicit information presentation affect and change the bias of estimators in cost estimating? An integrated model – the information uncertainty continuum – will also be proposed at the end.

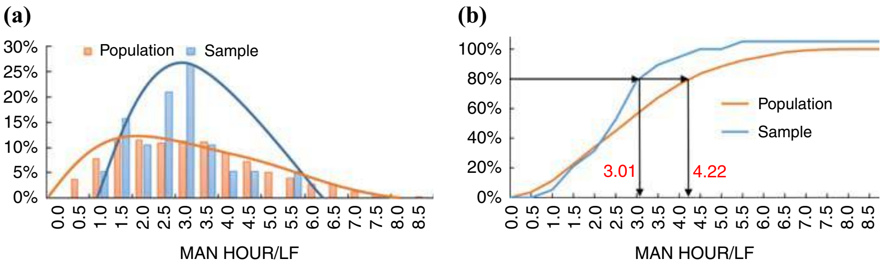
## Experiment 1: sampling error

*Motivation and hypothesis*

The first step of decision making under uncertainty is to gather information. If data accessibility is limited, sampling errors could happen. Various sampling error models claim that reliance on small samples is one factor that contributes to the attenuated influences of rare events in decision making (Hertwig *et al.*, 2004). It is generally due to the lack of accessible data, or more internally, individuals' limited ability in information recall (Hau *et al.*, 2010). It was found that when a sample size is not large enough, a person is more likely to under-sample rare events.

Sampling errors are more applicable when the studied probability distribution is asymmetric (Micceri, 1989). It echoes the reality of capital project cost estimating, which is essentially an estimation of construction productivity. Evidence indicates that most construction productivity distributions are positively skewed – that is, they have longer right tails. Thus, construction literature claims the use of beta distributions to be a proper description of construction productivities (AbouRizk *et al.*, 1994; Schexnayder *et al.*, 2005). The positive skew of a $\beta$ distribution creates a unique sampling error scenario in construction productivity estimating – planners tend to systematically and unintentionally underweight events pertaining to worse productivities. Figure 1 is produced based on a hypothetical Monte Carlo simulation to illustrate how different sample sizes can affect the perception of an estimator. Note that Figure 1 is only for demonstration purpose and the data are synthetic. A total of 1,000 data points were generated using a Monte Carlo simulation based on a pre-defined distribution function $X \sim 10 \times \beta$ (2, 5). Each round a random number was sampled from the distribution function. After a while, the aggregation of the generated samples should reproduce the original distribution. The blue curves show the perceived distribution (PDF and CDF) of a pipework activity when an estimator has the access to a fairly large number of samples ($n = 1{,}000$), while the blues curves indicate the perceived distribution of the same activity when the estimate only has the access to a small number of samples ($n = 20$). Figure 1(a) illustrates that the perceived probability distribution of pipework productivity based on 20 samples substantially differs from the actual PDF, and obviously presents shorter tails than is expected. Now, suppose the estimator decides to adopt a proper risk level in productivity estimating, such as the 80th percentile (i.e. the chance that the actual productivity would be worse than the estimated productivity is 20 percent). Due to the limited sample size, this conservative expectation can still lead to an aggressive estimate, as illustrated in Figure 1(b). This hypothetical example indicates that due to the sampling errors of insufficient data, the estimators tend to give aggressive estimates because small samples can hardly reflect the real shape of the original distribution.

Experiment 1 aims to investigate if sampling error affects the cost estimating accuracy, i.e. how the difficulty of acquiring enough information in capital project cost estimating affects the inductive process of probabilistic reasoning. It is worth noting that in real-world




**Notes:** (a) Probability density functions (PDFs); (b) cumulative density functions (CDFs). Data are synthetic, generated by a Monte Carlo simulation following the distribution function $X \sim 10 \times \beta(2, 5)$

**Figure 1.** Actual probability distribution (population) and the perceived probability distribution (sample, $n = 20$) of piping productivity

capital project cost estimating, different risk-taking strategies are preferred in different cases, such as using risk-averse strategies when the project is less competitive and profitability has a higher priority while using risk-seeking strategies when the bidding is more competitive with less anticipated profit. To better understand the impact of sampling errors in capital project cost estimating, both risk-taking strategies will be tested. As a result, experiment 1 will test the following hypotheses:

*H1a*. Increased sample size alleviates probability judgment bias in the risk-averse estimating scenario (i.e. when required to give risk-averse estimates).

*H1b*. Increased sample size alleviates probability judgment bias in the risk-seeking estimating scenario (i.e. when required to give risk-seeking estimates).

The judgment bias in our experiments (same thereafter) is measured as the absolute difference between the average estimates given by the subjects, and the actual population percentile values calculated based on the tested distribution $X \sim 10 \times \beta\ (2, 5)$. Therefore, our hypotheses will test if this absolute difference is reduced (or alleviated) by increasing the sample size, or the explicit level of information presentation.

*Experiment procedure*

In total, 60 ($n = 60$) project management students at Tongji University participated in the experiment (16 females; $M_{age} = 20.2$, SD = 0.6). The use of students in project management related experiments has been a well validated and widely used approach in recent publications, e.g., Alin *et al.* (2011), Iorio *et al.* (2012), Comu *et al.* (2014). Supporters claim that construction project management students have the desired background and knowledge in participating in these experiments. Meanwhile, since most of these students will become the industry practitioners, their motivation is also satisfactory.

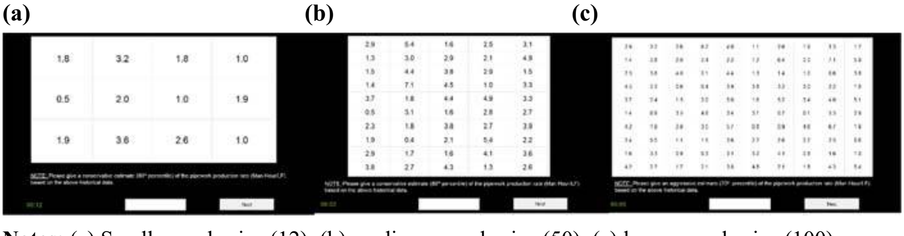
In our experiment, we made certain arrangements so that students would make estimates based on the good reasoning. First and foremost, all students had previously completed construction cost estimating courses and had sufficient knowledge about probability, estimating and productivity. Therefore, the students are qualified for the experiments. During the experiments, the students were provided with the background information, and were asked to make their estimates based on the best probabilistic reasoning. It was found that the students did not just give random estimates. Instead, they carefully checked the data and tried to make sound estimates since they were told that their performance in the experiments would be translated into bonus points on their final grades. The performance of the participants was evaluated based on the absolute difference between their estimates and the simulated (statistically reasonable) expected cost. According to Buehler *et al.* (1994), when the test subjects were motived to make accurate forecasts, they tended to "adopt an external approach to prediction, incorporating relevant distributional information," while when the test subjects were incentivized to finish task promptly, the test subjects tended to give optimistic time estimate. That is why the test subjects in our experiments were incentivized to give the most accurate estimates instead of the lowest estimates. In addition, prior to each experiment session, the rationale and procedure were introduced. We used these setups to ensure that the student subjects were working with their best knowledge and data.

We admit that professional estimators would be able to give better judgments. But our objective was to understand the fundamentals about the impacts of information presentation methods on estimating bias. If we can reveal that the variance of estimates can be attributed to the variance of information presentation methods (or information continuum), then our study would be a contribution to the discipline and it deserves further investigation, especially with professional estimators.

Participants played a computer-based task in which they were required to give an estimate for pipework productivity of a hypothetical project using on previous productivity data displayed on the screen (Figure 2). Depending on how many data points were shown on the screens, participants were divided into three groups, namely, the small sample size (12 numbers) group ($n=20$), the medium sample size (50 numbers) group ($n=20$), and the large sample size (100 numbers) group ($n=20$). For each of the group, a corresponding number of samples were randomly drawn from a beta distribution $X \sim 10 \times \beta$ (2, 5) to represent the positively skewed distribution of productivity (man hour/LF) that is observed in most pipework activities.

To get rid of the potential learning effects, between subject design was used in experiment 1, i.e. three groups of participants were tested with different factors (three levels of sample sizes) separately (Charness *et al.*, 2012). Each participant was required to review a set of numbers shown on the screen and give an estimated productivity for the hypothetical pipework activity. The numbers were randomly drawn from $10 \times \beta$ (2, 5), and were different for each participant. There were only two trials for each participant. To simulate the varying risk-taking strategies in real-world practices, each participant was required to give productivity estimates under two risk-taking scenarios – a risk-averse estimating scenario (or $P_{80}$ scenario hereafter) and a risk-seeking estimating scenario (or $P_{20}$ scenario hereafter). In the risk-averse estimating scenario, participants were asked to provide an estimate that represents the 80th percentile of the observed data, i.e. $P_{80}=P(X\leqslant x)=0.8$. While in the risk-seeking estimating scenario, participants were asked to review the same set of data and give the estimate representing the 20th percentile, i.e. $P_{20}=P(X\leqslant x)=0.2$. Instructions were given to all participants prior to the experiment.

After a participant entered the estimated productivity, she will submit the answers and advance to the next trial. Time was unlimited but was documented and shown on the screen. To incentivize participants, they were told that bonus points to their class grades would be given based on the accuracy of their estimates. The students who participated in the experiments were taking a project management course at Tongji University. One of the learning outcomes of this course was to understand the decision biases in project planning. As a result, this experiment was designed as a compulsory component of the syllabus to test if the students succeeded in this particular learning outcome, i.e. if they understood the biases in project planning. Therefore, the performance of the students in this experiment shall be reflected in their final grades. The students were notified about this experiment at the beginning this course, and were all required to participate. With that being said, this experiment was an in-class exercise according to the syllabus and all students were treated fairly. In addition, assigning bonus points to final grades is widely used to incentivize student-based experiments in the literature, such as (Burrowes, 2003; Ferrari and Mcgowan, 2002; Michel *et al.*, 2009). It has been confirmed to be an effective and ethical practice in student-based experiments.




**Notes:** (a) Small sample size (12); (b) medium sample size (50); (c) large sample size (100)

**Figure 2.**
Examples screenshots of experiment 1

*Results and discussion*

Estimates given by three groups of participants were compared using *t*-tests. Figure 3 illustrates the results.

Figure 3(a) depicts the comparison of risk-averse estimates (i.e. $P_{80}$ scenario) given three levels of sample size. It indicates that when required to give a relatively risk-averse estimate, participants who were given large sample sizes tended to be more conservative in their estimates compared to the small sample size group ($t(57) = -4.02$, $p < 0.05$, $d = 0.70$, $M_{small} = 3.88$, $M_{large} = 4.58$). Similarly, significant differences between the medium sample size group and the small sample size group were also observed ($t(57) = -3.04$, $p < 0.05$, $d = 0.53$, $M_{small} = 3.88$, $M_{medium} = 4.41$). However, no significant differences were observed between the medium sample size group and the large sample size group ($t(57) = -0.98$, $p = 0.33$, $d = 0.17$, $M_{medium} = 4.41$, $M_{large} = 4.58$), suggesting the influence of sample size on the estimate is attenuated beyond a certain point. Figure 3(b) depicts a comparison of risk-seeking estimates (i.e. $P_{20}$ scenario) given three levels of sample size. Results show that the influence of sample size on the estimates under risk-seeking strategy tends to be lower. Specifically, no significant differences were observed between the small sample size group and the medium sample size group ($t(57) = 1.53$, $p = 0.13$, $d = 0.19$, $M_{small} = 1.66$, $M_{medium} = 1.47$), or between the medium sample size group and the large sample size group ($t(57) = 1.12$, $p = 0.27$, $d = 0.14$, $M_{medium} = 1.47$, $M_{large} = 1.34$). Differences between the large sample size group and the small sample size group, on the other hand, were significant ($t(57) = 2.65$, $p < 0.05$, $d = 0.32$, $M_{small} = 1.66$, $M_{large} = 1.34$).

Figure 3(c) plots the least square means of combinations of all estimates under both risk-taking scenarios and three levels of sample sizes. It indicates the general trend of participants' estimates over the sample size: when the sample size decreases, estimates that are supposed to reflect risk-averse strategies become more aggressive than it deserves,

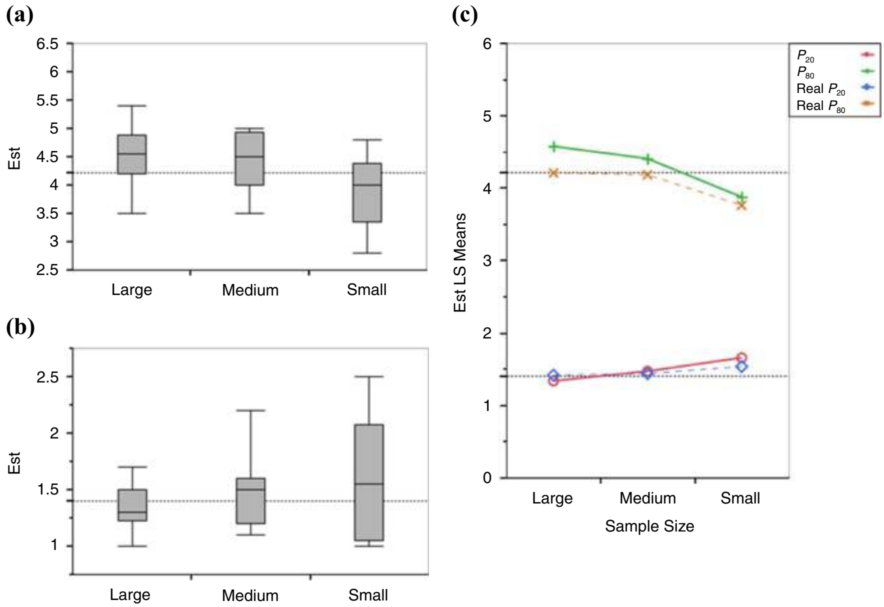



**Figure 3.** Estimated productivity (man hour/LF) under three levels of sample size

**Notes:** (a) Risk-averse estimates ($P_{80}$ scenario); (b) risk-seeking estimates ($P_{20}$ scenario); (c) mean estimates while risk-seeking estimates become more conservative than they are supposed to be. Figure 3(c) also shows that as sample size increases, the deviation between estimates and the real average $P_{80}$ value of the given data becomes larger when participants were required to give a risk-averse estimate. They tended to be overly conservative when exposed to a large sample size. To be noted, the real $P_{80}$ and $P_{20}$ values were drawn from the samples, not the population. In other words, since the sample sizes in the experiments were different, the sample $P_{80}$ and $P_{20}$ values were also different.

The results of experiment 1 indicate that the fundamental theses of prospect theory and the sampling errors effect both hold. The sampling errors effect suggests that when the sample size is not enough, people experience fewer extreme events and thus underestimate the occurrence of them in their probabilistic reasoning. Our results (Figure 3(c)) indicate that when moving from a large sample size to a small sample size, where the real $P_{80}$ values are becoming smaller, so do the participants' estimates. Meanwhile, the real $P_{20}$ values become larger and correspondingly, the estimates given by the participants are also bigger. The participants' estimates seem to follow the same trend of sampled percentile values.

We also noticed that in the large sample size group, under the risk-averse estimating scenario, participants gave estimates that were significantly more conservative than the real $P_{80}$ value ($t(38) = -2.62$, $p < 0.05$, $d = -0.37$, $M_{est} = 4.58$, $M_{real} = 4.21$). In other words, participants overly weighed the extreme events (i.e. really big productivity values). This observation echoes the thesis of prospect theory. Prospect theory argues that when people are making decisions under description, they incline to overestimate extreme events. The large sample size group in experiment 1 can be considered as a description-based decision given the fact that participants were exposed to the near-real distribution information. In this situation, participants did overweight extreme events.

However, in the risk-taking scenario (i.e. $P_{20}$ scenario), our findings do not support prospect theory. It may be attributed to the different decision heuristics owing to the varying numerical magnitudes of the observed numbers: evidence shows that people are more sensitive to bigger numerical values and, thus, may anchor more to the big numbers (Capaldi, 2010; Wong and Kwong, 2000). Meanwhile, it was also found that people tend to pay more attention in their decision making to situations that represent high variance (Manohar and Husain, 2013). It implies that participants in experiment 1 might have paid more attention to higher productivity values when they were reasoning the percentile values, compared to lower productivity values, because the same level of variance looks bigger when the base value is bigger (e.g. $6.0 \times 10$ percent $> 1.0 \times 10$ percent). As a result, the observations made in the risk-averse estimating scenario reflect participants' real decision heuristics better.

Results of experiment 1 indicate that *H1a* (risk-averse scenario) should be rejected. In the risk-averse scenario, although the aggressiveness bias has been reduced by increasing sample size, it soon transitions to a conservativeness bias owing to the cognitive process described by the prospect theory. Interestingly, *H1b* (risk-seeking scenario) is valid. Although the prospect theory could still take place, its influence seems to be alleviated by a numerical value anchoring effect that deserves a further investigation.

It should also be noted that in the rise-averse scenario, the variance of the estimates was much reduced as the sample size increases (i.e. from small to large). It indicates that when the test subjects were provided with more data points, their judgments tend to converge into a single level. This might be a natural consequence of the law of large numbers, a statistical phenomenon that when sample size increases, the average of the results obtained from a large number of trials should be close to the expected value, and will tend to become closer as more trials are performed (Seneta, 2013). As a result, the test subjects were exposed to information more relevant to (and closer to) the expected values. But we do not know if there is also any psychological process related to this, which deserves a further investigation.

## Experiment 2: recency effect

*Motivation and hypothesis*

To address data insufficiency issues, many industry associations and government agencies started to advocate data sharing and referencing in capital project cost estimating. The Construction Industry Institute in the USA initiated a benchmarking and metrics program in 1984 and has been collecting and sharing productivity information of capital projects for more than 30 years. The UK Government and APA also systematically employs the RCF method as part of project cost estimating, i.e. basing adjustments on data from past projects (Treasury, 2003a, b). However, the sequential nature of the experience-based decision still makes it vulnerable to the recency effect, i.e. people's inclination to assign greater importance to more recent events (Jarvik, 1951). When a planner acquires information, it will be stored in memory in some manner for decision making. Given that extreme events are uncommon, there is little chance that they would have occurred recently. If the assumption of the recency effect holds, increasing sample size in information learning will not benefit the decision making as it is assumed to (Camilleri and Newell, 2013). Experiment 2 will investigate if the recency effect can be observed in cost estimating. The hypotheses are:

*H2a.* Subjects assign bigger weights to the most recent information in their probabilistic reasoning in the risk-averse estimating scenario.

*H2b.* Subjects assign bigger weights to the most recent information in their probabilistic reasoning in the risk-seeking estimating scenario.

*Experiment procedure*

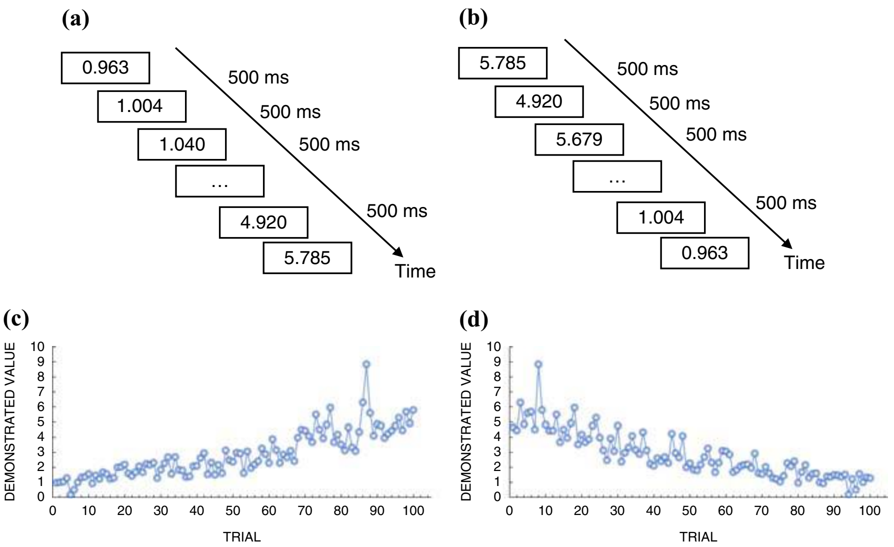
Forty ($n = 40$) project management students at Tongji University participated in experiment 2 (12 females; $M_{age} = 21.3$, $SD = 0.6$). Participants were required to estimate the productivity (man hour/LF) of a hypothetical pipework based on numbers shown on the computer screen. But instead of showing all numbers at once, they were shown 100 numbers sequentially, with a time interval of 500 milliseconds. To test, if the recency effect exists, two display sequences were used, namely an ascending scenario and a descending scenario, as illustrated in Figure 4. For both display scenarios, the noise was added to show "randomness" to the participants.

Participants were divided into two groups in accordance with the two display scenarios ($n = 20$ each). The numbers were once again randomly drawn from $10 \times \beta$ (2, 5). Two risk-taking scenarios – a risk-averse estimating scenario (i.e. $P_{80}$ scenario) and a risk-seeking estimating scenario (i.e. $P_{20}$ scenario) – were used in experiment 2 as well. Participants were asked to observe the numbers shown on the screen first (total time 50 s), and then to type in a risk-averse estimate and a risk-seeking estimate, respectively, based on their memories of the data. To incentivize participants, they were told that bonus points to their class grades would be given based on the accuracy of their estimates.

*Results and discussion*

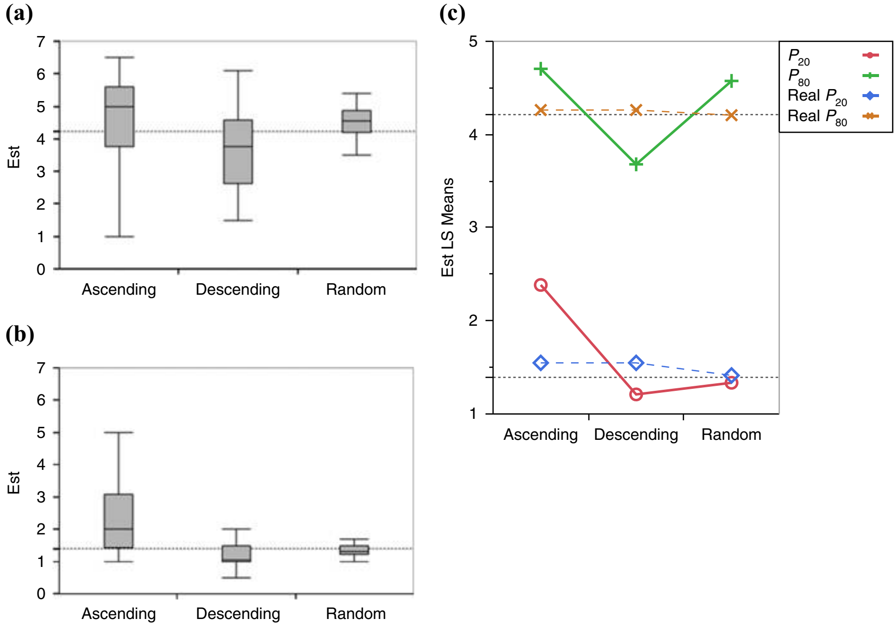
Estimates given by two groups of participants were compared using *t*-tests. Figure 5 illustrates the results.

Figure 5(a) and (b) depict comparisons of risk-averse and risk-seeking estimates (i.e. $P_{80}$ and $P_{20}$ scenario) given two display scenarios – ascending and descending. The results of large sample size group in experiment 1, labeled as "random," were included only for reference purposes. Results indicate that, in both risk-averse estimating and risk-seeking estimating scenarios, estimates of two groups were significantly different. When required to give a relatively risk-averse estimate, participants who were shown numbers in ascending




**Notes:** (a) Ascending scenario; (b) descending scenario; (c) ascending Scenario – noise added; (d) descending Scenario – noise added

**Figure 4.**
Display 100 numbers in different sequences




**Notes:** (a) Risk-averse estimates ($P_{80}$ scenario); (b) risk-seeking estimates ($P_{20}$ scenario); (c) mean estimates

**Figure 5.**
Estimated productivity (man hour/LF) under three display scenarios

sequence tended to be more conservative in their estimates ($t(38) = -2.40$, $p < 0.05$, $d = -1.03$, $M_{ascending} = 4.71$, $M_{descending} = 3.68$). Similarly, significant differences between the two groups in the risk-seeking estimating scenario were also observed ($t(38) = -3.76$, $p < 0.05$, $d = -1.18$, $M_{ascending} = 2.39$, $M_{descending} = 1.21$).

Figure 5(c) shows the least square means of all estimates under both risk-taking scenarios and two display scenarios. It indicates that, in the ascending display scenario, risk-averse estimates were more conservative than they were supposed to be ($t(37) = -2.86$, $p < 0.05$, $d = -0.69$, $M_{est} = 4.90$, $M_{real} = 4.21$), as well as risk-seeking estimates ($t(38) = -3.28$, $p < 0.05$, $d = -0.97$, $M_{est} = 2.39$, $M_{real} = 1.41$). In contrast, in the descending display scenarios, both risk-averse ($t(38) = 1.77$, $p < 0.05$, $d = 0.53$, $M_{est} = 3.68$, $M_{real} = 4.21$) and risk-seeking ($t(38) = 2.06$, $p < 0.05$, $d = 0.20$, $M_{est} = 1.21$, $M_{real} = 1.41$) estimates were too aggressive, compared to the real percentile values.

Results of experiment 2 validate both *H2a* and *H2b*, i.e. participants did assign bigger weights to the most recent information received in their probabilistic reasoning, with a large sample size ($n = 100$). It aligns with the theory of the recency effect and explains why capital project cost estimating remains aggressive given improved access to data: although overall data are more accessible, decision makers still rely on the most recent data, where extreme events (such as really worse productivity) are less experienced. Thus, the sampling errors effect still applies.



## Experiment 3: information format

*Motivation and hypothesis*

Several behavioral experiments indicate that probabilities are estimated differently by people as a function of information format (Camilleri and Newell, 2013). In description-based decisions, statistical information is more explicitly provided and represented as the likelihood or absolute frequency of events, while in experience-based decisions, people encounter samples without an explicit synopsis of events' probabilities (Camilleri and Newell, 2013; Hau *et al.*, 2010). Without an explicit description, mental representation of statistical information can vary on a personal basis (Hau *et al.*, 2010). Although there is an ongoing debate on the specific impacts of information format on risk decision making, there is a general agreement that different formats trigger different cognitive processes (Camilleri and Newell, 2013; Hau *et al.*, 2008).

For capital projects, various government agencies and industry organizations have recommended the use of explicit probabilistic information in cost estimating, such as the RCF method (Flyvbjerg, 2005, 2013). It is suggested that estimators should follow three steps to improve their estimates: identify a relevant reference class of past, such as similar projects; establish a probability distribution for that class; and compare the specific project to reference class' distribution (Flyvbjerg, 2013). It is argued that explicit probabilistic information is expected to significantly improve estimating accuracy (Flyvbjerg, 2008; Lovallo and Kahneman, 2003).

However, it should be noted that when explicit probabilistic information is provided, it is indeed description-based decision making. In this case, prospect theory would predict the other type of bias – overly conservative decisions by overestimating extreme events (Kahneman and Tversky, 1979), which should also be avoided in cost estimating. There is clearly a gap between RCF's central argument and the findings of prospect theory. To provide more evidence, this experiment will test the following hypothesis:

*H3a.* Explicit statistical information alleviates probability judgment bias in the risk-averse estimating scenario.

*H3b.* Explicit statistical information alleviates probability judgment bias in the risk-seeking estimating scenario.

*Experiment procedure*

In total, 20 ($n = 20$) project management students at Tongji University participated in the experiment (4 females; $M_{age} = 19.5$, $SD_{age} = 0.9$). Participants played a computer-based task where they were required to give the productivity estimate (man hour/LF) of a hypothetical pipework based on a PDF curve displayed on the screen (Figure 6). It is assumed that PDF curves serve as an explicit display of statistical information. In contrast, the tabular display of numbers, as used in experiment 1, refers to an implicit display. The PDF curve was generated based on the same beta distribution $X \sim 10 \times \beta$ (2, 5) used in experiments 1 and 2. Similar to experiments 1 and 2, both a risk-averse estimating scenario ($P_{80}$ scenario) and a risk-seeking estimating scenario ($P_{20}$ scenario) were tested. Results from experiment 3, including the results of all three sample size groups (small, medium and large), were used in the analysis to compare the difference in productivity estimating given explicit display vs implicit display.

*Results and discussion*

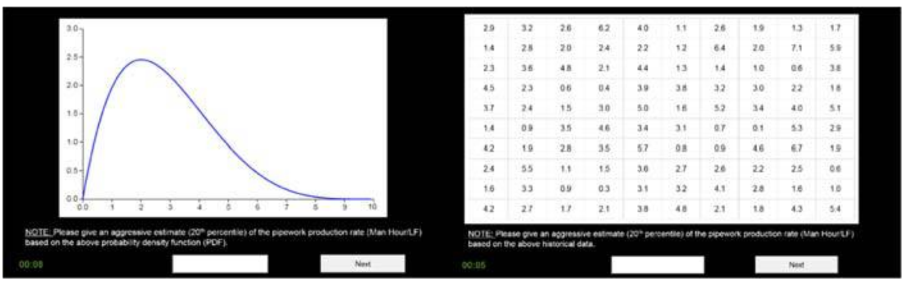
Estimates given by four groups of participants were compared using *t*-tests. Figure 7 illustrates the results.

Figure 7(a) depicts the comparison of risk-averse estimates (i.e. $P_{80}$ scenario) given four information formats, namely explicit, large (table), medium (table) and small (table). The result shows that in the risk-averse estimating scenario, estimates of the explicit group were significantly different from small table group ($t(38) = -6.03$, $p < 0.05$, $d = -0.9$, $M_{explicit} = 4.78$, $M_{small} = 3.88$) and medium table group ($t(38) = -2.88$, $p < 0.05$, $d = -0.37$, $M_{explicit} = 4.78$, $M_{descending} = 4.41$); it seems that with explicit statistical information, participants tended to give overly conservative estimates than the small and medium table groups. While there was no significant difference between the explicit group and the large table group ($t(38) = -1.23$, $p = 0.22$, $d = -0.20$, $M_{explicit} = 4.78$, $M_{large} = 4.58$).

Figure 7(b) shows the comparison of risk-seeking estimates (i.e. $P_{20}$ scenario) given four information formats. Estimates of the explicit group were not significantly different from any of the table groups (Explicit vs small table: $t(38) = 1.39$, $p = 0.17$, $d = 0.22$, $M_{explicit} = 1.44$, $M_{small} = 1.66$; Explicit vs medium table: $t(38) = 0.26$, $p = 0.79$, $d = 0.03$, $M_{explicit} = 1.44$, $M_{medium} = 1.34$; Explicit vs large table: $t(38) = -1.02$, $p = 0.31$, $d = -1.05$, $M_{explicit} = 1.44$, $M_{large} = 1.34$).

Figure 7(c) shows that in the risk-averse estimating scenario, as statistical information becomes more explicit, i.e. moving from small sample size ($n = 12$) to medium ($n = 50$) and large sample size ($n = 100$), and ultimately to a graphic display of the PDF curve, estimates become increasingly conservative, and started to deviate from the real $P_{80}$ value significantly.

(a) (b)




**Notes:** (a) Explicit statistical information – graphic display; (b) implicit statistical information tabular display (done in experiment 1)

**Figure 6.** E example screenshots of experiment 3

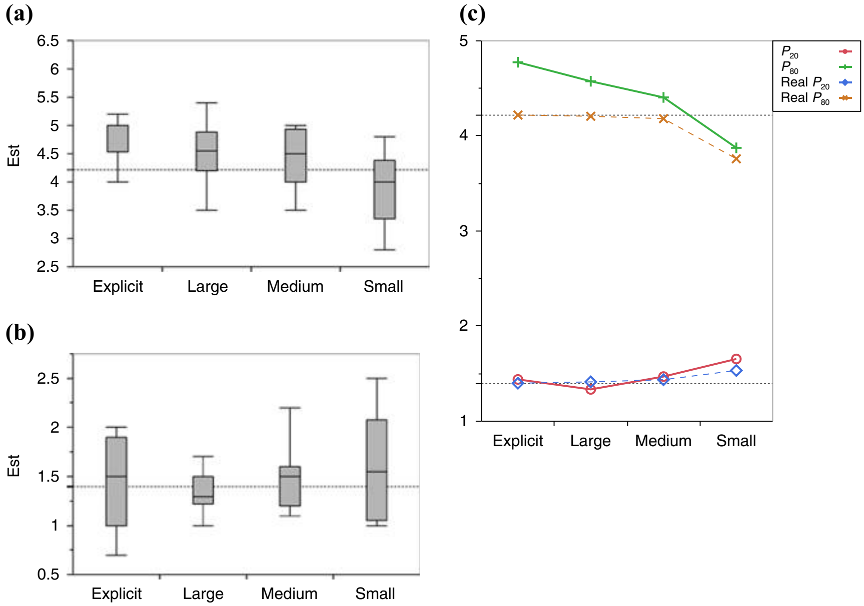



**Figure 7.** Estimated productivity (man hour/LF) under four information formats

**Notes:** (a) Risk-averse estimates ($P_{80}$ scenario); (b) risk-seeking estimates ($P_{20}$ scenario); (c) mean estimates

In the explicit group (i.e. graphic display of PDF curve), participants gave estimates that were significantly more conservative than the real $P_{80}$ value ($t(38) = -7.05$, $p < 0.05$, $d = -0.57$, $M_{est} = 4.78$, $M_{real} = 4.21$). Given the fact that the presence of explicit statistical information is considered as a description-based decision (Camilleri and Newell, 2013), it once again proves the central thesis of the prospect theory, i.e. people tend to overweight the extreme events, or really bad productivity in our experiment. However, similarly to what observed in experiment 1, such a trend cannot be observed in the risk-seeking estimating scenario. Whether it owes to the different decision heuristics when people are facing big numerical values and small numerical values, as suggested by Capaldi (2010), requires further investigation.

The results of experiment 3 indicate that *H3a* should be rejected. In the risk-averse scenario, although the aggressiveness bias has been corrected by moving to a more explicit statistical information display, it is also transitioning to a conservativeness bias as predicted by the prospect theory. Nonetheless, *H3b* is supported as if the influences of the prospect theory are compensated by a numerical value anchoring effect that deserves a further investigation.

## General discussion

The setups of the three experiments can be seen as a continuum of uncertainty in information in probabilistic reasoning. The small sample size group in experiment 1, for example, was only exposed to limited samples ($n = 12$) drawn from an unknown distribution, while on the other end of the continuum, the group in experiment 3 could rely their probabilistic reasoning on the explicitly displayed statistical information in the form of a PDF curve. Between the two groups, gradually increased sample size simulates the situation where more information about the probability distribution is obtained.

Our experiment results suggest that across this continuum, the nominal risk attitudes of decision makers, or the appeared risk-taking behavior, could change substantially: when decisions are made from experience, extreme events seem to be under-weighed. However, this bias can transition into a bias of overestimating extreme events in description-based decisions. We use Figure 8 to illustrate this transition across information continuum. It supports the central theses of both the prospect theory and the decisions from experience theories (Camilleri and Newell, 2013; Hau *et al.*, 2008; Kahneman and Tversky, 1979). More specifically, when decisions are made from descriptions, a reflection effect is expected to be observed where people incline to overestimate extreme events (Kahneman and Tversky, 1979); when decisions are made from experience, a reverse reflection effect can be observed, where people's attitude toward extreme events is reversed (Ludvig and Spetch, 2011). Overall, the sampling errors effect (Camilleri and Newell, 2013) can possibly explain the transition across this information continuum, as shown in Figure 8, the real percentile value (in the risk-averse scenario) of observed data keeps increasing, reflecting the fact that more extreme events are sampled by increasing sample size. Correspondingly, the subjective estimate also increases. The recency effect (Jarvik, 1951) shows a similar influence as the sampling errors effect. Furthermore, when the continuum moves to the regime of description, a weighted utility function per the prospect theory shall predict the overestimation bias (Kahneman and Tversky, 1979).

However, it was also found in our experiments that this information uncertainty continuum seems to have less impact on people's attitude toward extreme events when they were asked to give risk-seeking estimates: although the reverse reflection effect could still be observed in experience-based decisions, possibly attributed to the sampling error effect or the recency effect, the reflection effect as predicted by the prospect theory was not seen in our experiments. Instead, participants seem to give fairly accurate estimates of probabilities when the explicit description of statistical information was provided. It is possible that certain cognitive processes are counteracting the influence of the reflection effect when decision makers are making probability estimates based on data with smaller numerical values. It could be related to the variability of decision heuristics pertaining to numerical values (Capaldi, 2010).

Overall, this information uncertainty continuum provides a promising explanation to the aggressive cost estimating observed in most capital projects. Cumulative evidence indicates that key decision makers are usually risk-averse, or risk-neutral in project planning (Han *et al.*, 2005). Risky decisions are often considered reckless and less favored in project management.

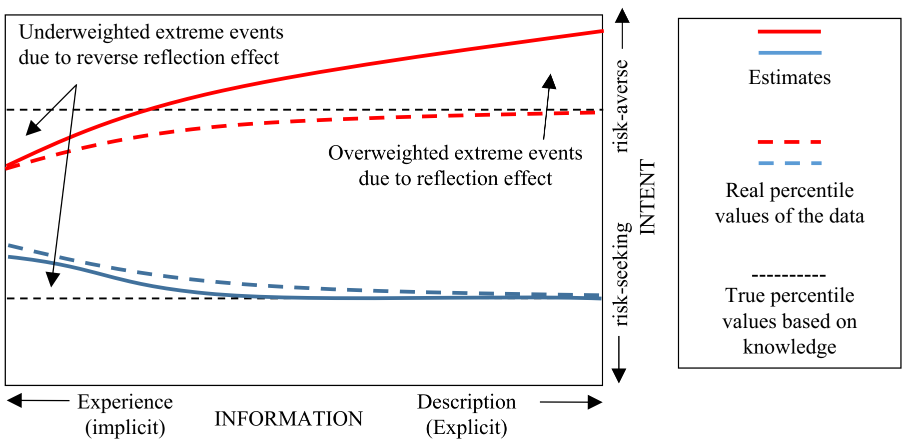



**Figure 8.**
Nominal risk attitudes of decision makers change across the statistical information continuum

A recent research study indicates that a moderate risk-averse attitude indeed leads to a bigger chance of success in competition in the construction industry (Kim and Reinschmidt, 2010). It is likely that industry practitioners are adopting a proper level of risk-taking in their decision making. The intention of industry practitioners may be to stay in the upper quadrants (more conservative) rather than the lower quadrants (more aggressive), as seen in Figure 8. Yet, individuals' imperfect capability to process uncertainty of information, as well as the general lack of data sharing, completely distort the apparent risk attitude. A decision maker may still want to make a risk-averse decision, but because she is likely to make decisions from experience, the reverse reflection effect eventually transforms her original conservative decisions into aggressive ones. As illustrated in the upper left quadrant of Figure 8, it refers to overly optimistic estimates than they are supposed to be in capital project cost estimating. Obtaining more data, or providing more explicit statistical information, will help to move the index to the center of the information continuum and correct the bias. But as more data becomes accessible, the industry practitioners will need to be careful about the other bias – over conservativeness. On the other hand, we notice that this information continuum does not affect the nominal risk attitude in the risk-seeking scenario as significantly as in the risk-averse scenario, or it has less impact on the estimators' risk attitude when they are more risk-seeking. When industry practitioners are risk-averse in estimating, it will not affect the validity of the proposed information continuum theory.

## Conclusions and limitations

In this study, we found that imperfect information, combined with human's imperfect ability to process uncertainty of information, could significantly affect the nominal risk attitude of capital project planners. As illustrated in Figure 8, the decision bias is significantly changed when the given information ranges from complete and explicit to incomplete and implicit. The result echoes our original statement that incomplete information could change decision bias. The findings of our experiment indicate that the sampling errors (i.e. bias due to insufficient samples) often encourage aggressive judgments. The impact is further amplified by the impacts of the recency effect, i.e. the inclination to assign bigger weights to the most recent experience, as well as the impact of how explicit the information is presented to the test subjects. We also found that when the intention was to make risk-averse decisions, the main arguments of the prospect theory and the paradigms of the description–experience gap were supported. But when the test subjects were required to make risk-seeking decisions, prospect theory does not seem to be a strong predictor of what we observed in the experiments. Specifically, the reflection effect was not seen as predicted by the prospect theory.

Accurate cost estimating is critical to the success of a capital project. Aggressive and biased cost estimating in capital projects is a well-documented, long-lasting problem worldwide. Many agencies, such as the UK Government and the APA, have recognized the importance of understanding the root causes of aggressive decisions in capital project estimating. This study is an effort of investigating this issue from the decision psychology perspective, i.e. how different presentations of the same information affect the perception and judgment of the estimators in capital projects. As a result, this study represents a research effort of significance to the capital project management practices.

The theoretical contribution of this study lies in providing a new theoretical dimension to the analysis and prediction of estimating biases in capital projects, or the so-called "information continuum." Information continuum quantifies how explicit the project information is presented to the estimators, and its implications for reshaping the nominal risk attitude. Planning can be seen as making decisions for future events. Thus, it is fraught with uncertainty. It is extremely important to understand the fundamentals about risk decision making under imperfect information. Although existing planning literature has examined this theme from risk attitude perspective (Han *et al.*, 2005), this study further investigates the information induced distortion mechanism when a proper level of risk attitude is adopted. The proposed information uncertainty continuum model provides a simple yet strong theoretical basis for forecasting and compensating planning bias. To our best knowledge, there is few research focusing on understanding the most proper way of presenting project data to the key decision makers (e.g. the formats and the amount of historical project information) to reduce or eliminate decision biases. Our findings indicate that there is a really complex psychological process pertaining to the information taking and cost estimating in capital projects, which can hardly be explained by a single theoretical framework. To be more specific, the holistic analysis of the decision bias in capital project estimating should be done by integrating a series of interdependent theoretical frameworks, including the prospect theory, description–experience gap, recency effects and the specific risk-decision scenarios, into a comprehensive analytical framework about information presentation, or the information continuum. It is expected to advance our understanding about inaccuracy or biases of capital project planning by exploring the most fundamental level of estimating decision-making pertaining to the individual level reasoning and judgement process.

The future agenda is related to several limitations in this study. First, for each experiment session, the numbers of participants were limited, making the results more indicative. One of the future works will be increasing the number of test subjects to yield more statistically sound results. Second, as mentioned above, while we decided to select students to participate the experiment for the validity of the method has been tested and confirmed, experiments with industry workers and practitioners could further validate our findings. Third, it is still unclear why the impact of the information continuum is less in the risk-seeking estimating scenario. It may be caused by the different numerical magnitudes presented to the test subjects. For example, although "1m" and "1,000,000" refer to the same number, previous literature (Capaldi, 2010) has shown that different numerical presentations can affect the perception of the test subjects differently. An investigation into the cognitive process driven by different numerical magnitudes is needed. Last, risk-taking scenarios appear to be an influential factor in the nominal risk attitude prediction. While our experiments only tested two extremes of risk taking, including risk-averse estimating and risk-seeking estimating. A broader test of the risk-taking attitude on the complete information continuum model, as illustrated in Figure 8, is needed.



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