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Impacts of human communication network topology on group optimism bias in Capital Project Planning: a human-subject experiment

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ABSTRACT

Capital projects are critical to the world's economy. Despite the advancement of prediction techniques, capital projects still suffer from overly optimistic plans, i.e. tight budgets and schedules. This article focuses on understanding this issue from the perspective of optimism bias, i.e. a psychological bias toward the inclination to be overly optimistic about the chance of success. We hypothesize that human communication network topologies are strong predictors of harmful optimism bias at the group level in project planning. A human-subject experiment was performed to test group optimism bias levels under different communication network topologies. We recruited 103 subjects to estimate the cost of an artificial power plant project. The communication networks were manipulated to reflect different topologies. The subjects' estimates were compared to a Monte Carlo simulation result based on real historical data to quantify the level of optimism bias at the group level. Preliminary results find that certain human communication network topology leads to more realistic estimates, possibly due to a process of updating individual judgement based on peers' judgements. The findings of this study are expected to urge further theoretical investigations into the development of simple yet effective decision support systems to reduce decision-making bias in capital project planning.

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Communication network; optimism bias; project planning; topology

Introduction

Capital projects, such as roads, bridges and utility systems, are the foundation of the world's economy. World spending 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). However, it is almost axiomatic that capital projects come in late and over budget, rarely living up to expectations (Bordat *et al*. 2004, Ahiaga-Dagbui and Smith, 2014a, Flyvbjerg 2006, 2017, Flyvbjerg *et al*. 2009, Karimi *et al*. 2017, Locatelli *et al*. 2017). Data shows that more than 90% of these projects experienced severe cost and time escalation; the average cost overrun was 28% and most were at least 120 days behind schedule (Bordat *et al*. 2004). Another study of a century of completed capital projects has confirmed that the overrun issue has not improved over the last century, or across different geographic regions (Figure 1) (Flyvbjerg *et al*. 2003). Losing control over capital projects has led to misuse and inefficient management of scarce public resources. A recent survey of more than 300 megaprojects indicates that 65% of industrial projects worldwide with budgets larger than $1 billion USD failed to meet their business objectives (Merrow 2011).

A number of explanations exist for the observed capital project overruns (Lind and Brunes 2015). The most common theory attributes overrun issues to political and organizational pressures, such as competition for scarce funds or jockeying for position, and to lack of incentive alignment (Flyvbjerg 2004). Flyvbjerg and Wachs *et al*. described a phenomenon called "strategic misinterpretation", i.e. planners deliberately and strategically overestimate benefits and underestimate costs in order to increase the likelihood that it is their projects, and not the competition's that gain approval and funding (Wachs 1989, Flyvbjerg *et al*. 2005). Lovallo and Kahneman (2003) found that organizations tend to suppress pessimistic opinions and reward optimistic ones, where pessimism can be interpreted as disloyalty. Researchers have also examined the impact of technical difficulties in making predictions in capital projects on over-aggressiveness

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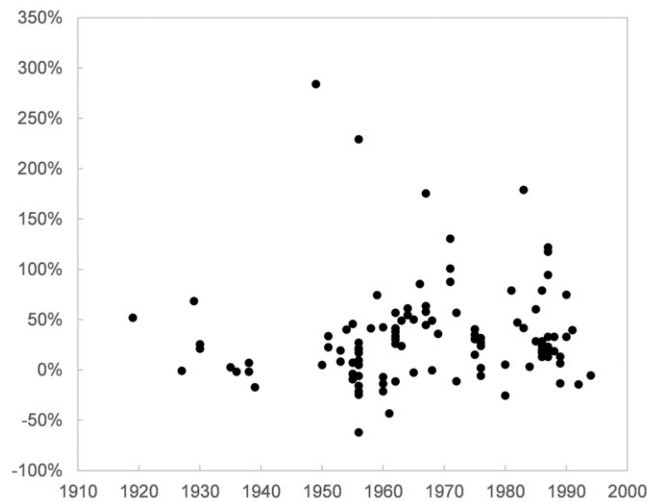

Figure 1. A survey of 111 completed projects shows that cost overrun has been a consistent issue for at least a century. Adapted from (Flyvbjerg *et al.* 2003).

(Flyvbjerg *et al*. 2005). Capital projects are inherently risky due to the long planning horizon and complex interfaces (Flyvbjerg *et al*. 2009). Decision-makers in these projects often have imperfect information due to unreliable or outdated data and the use of inappropriate statistical models (Vanston and Vanston 2004, Salling and Leleur 2015). The project scope or ambition level can change significantly during project development and implementation (Flyvbjerg *et al*. 2003, Al-Sabah *et al*. 2014, Alasad and Motawa 2015). Each of these contributes to the difficulty of making accurate predictions in capital projects (Khamooshi and Cioffi 2012).

Recent empirical investigation into this issue has revealed that *optimism bias*, i.e. a cognitive bias pertaining to people's inclination to be overly optimistic about the chance of success, may also contribute to overrun issues in capital projects (Flyvbjerg *et al.* 2003, Ahsan and Gunawan 2010, Raisbeck *et al.* 2010, Atkin 2012, Jennings 2012, Ahiaga-Dagbui and Smith 2014b). Productivity is typically overestimated in the planning phase of capital projects, causing insufficient funding and unrealistic schedules; risks are often underestimated, resulting in inadequate preparation and contingencies for plausible risk scenarios (Kahneman and Tversky 1979, Lovallo and Kahneman 2003, Jennings 2012, Flyvbjerg *et al*. 2009). Decision makers for the nation's most critical projects tend to "*make decisions based on delusional optimism rather than on a rational weighting of gains, losses and probabilities*" (Lovallo and Kahneman 2003). In other words, we are overrunning in capital projects because the initial plans are overly aggressive.

Optimism bias is a psychological phenomenon that encapsulates the systematic tendency for decision makers to be overly optimistic about the likelihood of positive events (Flyvbjerg *et al*. 2003, Raisbeck *et al*. 2010). When political and organizational pressure is well controlled, such as when a project has been awarded, the optimism bias better accounts for the biased plans in capital projects (Flyvbjerg 2008). The optimism bias in capital project planning has been seen as an impediment to prudent fiscal planning, for the government as a whole and for individual departments within government. To address this tendency, the UK government decided to systematically employ the *reference class forecasting* method as part of project appraisal for large transportation projects, i.e. basing adjustments on data from past projects or similar projects elsewhere (Treasury 2003a, 2003b). The American Planning Association (APA) in the US has also endorsed and recommended the reference class forecasting method (Flyvbjerg 2005, Flyvbjerg 2006). Despite efforts to cure optimism bias with better predictive models and additional information for decision-makers, the problem persists. There is still a pressing need to advance our understanding of the mechanisms of optimism bias in capital projects.

To date, research has focused on understanding, or even curing, harmful optimism bias at the individual level (Johnson *et al.* 1981, Schweitzer and Cachon 2000), such as understanding the neural basis of optimism bias (Sharot *et al.* 2011), or improving individual judgement by providing additional information about historical cases (American Planning Association 2005). Thus far, little has been done to address the group level optimism bias in capital projects, measured as the delta between group judgement and statistically realistic judgement based on historical data. The organizational science literature offers strong

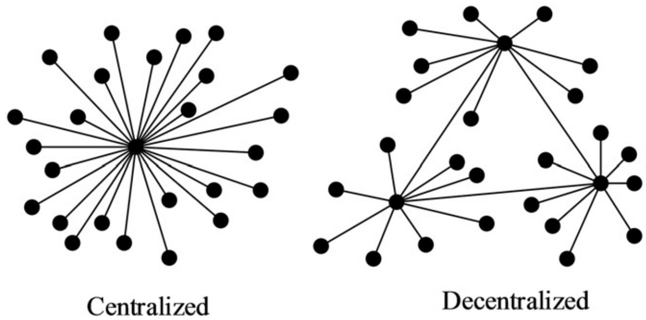

Figure 2. A decentralized communication network helps reduce errors when information is ambiguous or distributed among team members; while when information is complete, a centralized communication network improves group decision quality (Leavitt 1951, Shaw 1954, 1964, 1971).

theoretical and empirical evidence that human communication networks may serve as a medium of the individual-group optimism bias transition. Human communication networks are patterns of contact created by the flow of messages among communicated human agents through time and space (Monge and Contractor 2003). A fundamental discovery in this area is that people's decision-making is best predicted by examining the web of communications in which they are embedded (Katz *et al.* 2004). Numerous empirical investigations have proven network topology to be a significant predictor of the variance in group decision-making (Bavelas 1950, Bavelas and Barrett 1951, Leavitt 1951, Putnam *et al.* 1994, Sparrowe *et al.* 2001, Cummings and Cross 2003, Hwang and Lin 2012, Conaldi and Lomi 2013, Levine *et al.* 2013). Nonetheless, it depends upon a variety of contextual factors such as information completeness and timeliness, task complexity, and time pressure, etc. (Leavitt 1951, Shaw 1954, 1964, 1971) (Figure 2). The findings in human communication network studies imply the possible existence of a causal relationship between human communication network topology and collective optimism bias at the group level in capital projects.

This research aims to test the hypothesis that *the optimism bias at the group level in project planning is significantly affected by the communication network topologies*. To this end, we investigate the influence of human communication networks on the overly optimistic group decisions prevailing in capital projects as our study case.

Literature review

Optimism bias

Recent research efforts have begun to investigate the fundamental optimism bias that may contribute to unrealistic plans for capital projects. Optimism bias is defined as the difference between expectations and the outcome that follows; if expectations exceed reality, the bias is optimistic (Sharot 2011a). Evidence has confirmed the prevailing existence of optimism bias in human beings (Flyvbjerg 2008, Jennings 2012, Love *et al.* 2012, Flyvbjerg 2006). When people make judgements about important personal affairs, such as medical situations, financial investment and career development, more than 80% of the population anticipate encountering more positive events than they end up experiencing, regardless of gender, race, age and other demographic factors (Sharot 2011a, Sharot *et al.* 2007). Optimism bias is considered to be a natural result of evolution, because optimistic judgement encourages the pursuit of scarce resources and promotes the chance of success in competition (Sharot *et al.* 2007). It is thought to be vital to mental and physical health, and has been widely observed in relation to success in the professional domain as well (Puri and Robinson 2007, Johnson and Fowler 2011, Sharot 2011b).

However, optimism becomes harmful when extended to collective group decisions (Sharot 2011b). For instance, optimism bias has been identified as one core cause of the financial crisis of 2008 (Soros 2008, Duca *et al.* 2010, Roszkowski and Davey 2010, Miller and Rosenfeld 2010). Unrealistic expectations of individuals, financial analysts and government officials that the market would continue growing, despite evidence to the contrary, likely contributed to the collapse (Soros 2008, Duca *et al.* 2010, Miller and Rosenfeld 2010, Roszkowski and Davey 2010, Sharot 2011a, 2011b). Optimism bias has also been recognized as a major contributor to the unrealistic plans of many public-funded capital projects (Flyvbjerg *et al.* 2003). Productivity is often overestimated and risks are underestimated, causing insufficient funding, unrealistic schedules and inadequate preparation for plausible risk scenarios (Flyvbjerg *et al.* 2003, Ahsan and

Gunawan 2010). In the US, more than 90% of completed capital projects experience severe cost and time overruns due to unrealistic plans; on average, capital projects overran their budgets by 28% and time by 120 days (Flyvbjerg *et al*. 2003, Bordat *et al.* 2004). Given the world's tremendous spending on capital projects (The Economist 2008), unrealistic optimism can cause a significant misuse of scarce public resources.

To mitigate the potential damage introduced by optimism bias, various public agencies have advocated for methods or systems that provide additional information about historical projects, or similar projects elsewhere, to decision-makers, assuming that this will improve realistic judgements (Flyvbjerg 2008). However, evidence has presented a puzzle that undermines the rationale behind these efforts: optimism bias can be maintained in the face of reality (Sharot *et al.* 2011). People are known to maintain overly positive expectations despite a lifetime of experience with reality. For instance, highlighting previously unknown risk factors for disease is surprisingly ineffective at altering optimistic perceptions of individuals' medical vulnerability (Sharot *et al*. 2007, 2011). It has been found that optimism bias is maintained in the face of disconfirming evidence because people update their beliefs more in response to positive information about the future than to negative information about the future (Sharot 2011b). In a lab test (Sharot *et al*. 2011), researchers found that when participants estimated their probability of suffering from cancer as 10% and then learned that the average probability was 30%, they did not update their estimate much the second time around. However, if a person initially estimated the probability of suffering from cancer at 40% and then learned that the average probability was 30%, they substantially updated their estimate to more closely match the average probability. The selectivity of positive versus negative information has been found to correlate with the neural basis of the human brain (Sharot *et al*. 2007).

Another important question concerning optimism bias is: *How is individual optimism bias translated into collective optimism bias at the group level?* Literature addressing group polarization provides a useful theory for predicting the individual-collective optimism transition. Group polarization is a phenomenon in which members' initial preferences are amplified during a group process (Lovallo and Kahneman 2003) and is attributed to the inclination to develop shared mental models for better social identification (Mohammed *et al.* 2010). It also originates from situations in which people are reluctant to voice their concerns due to psychological safety considerations (Edmondson 1999). According to group polarization theory, if members individually are generally optimistic, group discussion makes them more optimistic and thus results in even more overly aggressive plans. Nonetheless, it is still unclear whether group polarization explains all the variance in observation data about capital projects, because evidence shows that group polarization can also be shown as *cautious shift* (rather than *risky shift*), which is rarely seen in capital projects (Myers and Lamm 1976, Sunstein 2002). An explanation is needed to account for the systematic shift of bias in capital projects.

Human communication network and group optimism bias

We propose to study the optimism bias in capital projects from the human communication network perspective. Since the 1950s, cumulative evidence has proven the critical role of communication network topology in individual and group decision-making (Leavitt 1951, Shaw 1954, 1964, 1971). One seminal study was carried out by Bavelas *et al.* at Massachusett Institute of Technology (MIT) (Bavelas and Barrett 1951). In a series of experiments, they manipulated the communication patterns among members of small groups by controlling who could send messages to whom; they then measured the impact of various patterns on group functioning and performance (Bavelas 1950, Bavelas and Barrett 1951). The researchers found that centralization – the extent to which one person serves as a hub of communication – had a significant impact on individual and group functioning (Bavelas 1950, Bavelas and Barrett 1951. The complexity of the task proved to be a critical moderating variable: centralization was beneficial when the task was simple and detrimental for complex tasks (Bavelas 1950). A decentralized structure was also best when information was distributed unevenly among group members, or when the information was ambiguous (Leavitt 1951, Shaw 1971). Following their work, a variety of disciplines (e.g. psychology, organizational science, and economics) have identified relationships between communication network topology and decision-making quality from different perspectives. Representative works include (Lipman-Blumen and Leavitt 1999, Sparrowe *et al.* 2001, Cummings and Cross 2003). Recent work addresses the mutual correlations between internal and external links (Haas 2003), on network topology and problem-solving efficiency (Kearns *et al.* 2006), and on using computer simulation to quantify the influence of network topology on decision-making quality (Fioretti 2013). Although targeting different research questions, i.e. decision-making efficiency and quality, human communication network topology may be an important medium for the individual-group optimism transition. We performed a preliminary study to evaluate the feasibility of our conjecture.

Human subject experiment

We conducted a human subject experiment to gain a preliminary understanding about how optimism bias at the group level is affected by the topology of communication networks in project planning. Preliminary results indicate that a significant correlation exists between network topology and collective optimism bias measured as the delta between the labour hour estimate given by human subjects and the Monte Carlo simulation result based on the historical data of 38 completed capital projects. The following section will introduce the experiment and findings.

Data preparation

Capital project planning is a multidisciplinary and multi-organizational process that builds on judgements made separately by different project functional units (Kerzner 2009). A formal boundary between responsibilities is established and leads to distributed decision processes (Thomsen *et al.* 2005). Even in the same functional unit, a project is often divided into groups of work, called crafts, which are handled separately by different planners, such as *concrete*, *mechanical systems* and *steel* (Globerson and Zwikael 2002). Ultimately, judgements made by separate decision makers will be aggregated by a third party, usually chief estimator, who puts together a final budget (Globerson and Zwikael 2002). In this process, one person's judgements may be affected by others', either formally or informally (Du and Bormann 2014). For example, a steel estimator may adjust the steel productivity prediction to accommodate the concrete pouring productivity prediction made by a concrete estimator, because there is a definite relationship between the two crafts (Du and Bormann 2014).

In this study, we propose that the need for communication between any two planners depends on the correlation between their respective crafts. Therefore, we collected the productivity data from 38 finished capital projects in the US, including the production rates of 26 major crafts. The 38 capital projects, all belonging to company "A," were built between 2002 and 2011, and were the same type of power plant project (gas turbine power plants). Since these projects were built by the same company and were of similar magnitude, the characteristics of these projects were similar. All projects were divided into 26 crafts, as shown in Table 1. Table 1 lists the crafts and their descriptions.

Table 1. Twenty six crafts used in the experiment.

ID	Craft	Description	Productivity (UOM)
A01	Concrete pouring	Concrete pouring, finishing and curing	Cubic yard/hour
A02	Concrete formwork	Installing concrete formwork	Square foot/hour
A03	Concrete reinforcing	Installing concrete rebar	Cubic yard/hour
A04	Embedded steel	Installing steels embedded in the structures	Ton/hour
A05	Structural steel	Erecting major steel structures	Ton/hour
A06	Grating	Installing grating	Square foot/hour
A07	Pipe racks	Installing pipe racks	Ton/hour
A08	Piping	Installing main system pipes	Linear foot/hour
A09	Underground piping	Installing underground pipes	Linear foot/hour
A10	Small bore piping	Installing small-bore pipes	Linear foot/hour
A11	Large bore piping	Installing small-bore pipes	Linear foot/hour
A12	Critical piping	Installing critical pipes (machinery)	Linear foot/hour
A13	Underground conduit	Installing underground conduits	Linear foot/hour
A14	Ground conduit	Installing above ground conduits	Linear foot/hour
A15	Cable tray	Installing cable tray	Linear foot/hour
A16	High voltage cable	Installing cables for >600V applications	Linear foot/hour
A17	Low voltage cable	Installing cables for <600V applications	Linear foot/hour
A18	Control cable	Installing control cables	Linear foot/hour
A19	Instrument cable	Installing instrument cables	Linear foot/hour
A20	Iso non seg bus	Installing isolated-phase non-segregated bus	Each/hour
A21	Lighting	Installing light fixtures	Each/hour
A22	Instrument handling	Handing and moving instruments	Each/hour
A23	Instrument test	Testing instruments	Each/hour
A24	Instrument install	Installing instruments	Each/hour
A25	Instrument calibration	Calibrating instruments	Each/hour
A26	Painting	Painting all pipes and architecture	Square foot/hour

We found that the production rates of these 26 crafts are interdependent, but at different levels. Figure 3 provides a complete visualization of the correlations among the 26 crafts in terms of productivity. The correlation analysis suggests that there is a natural need for the craft planners to communicate and cross-check their judgements. If two crafts are correlated in productivity, the planners will likely revise their original judgements based on updated information from each other. A complex network, as illustrated in Figure 3, may lead to a complex process of judgement updates. As a result, this study focused on the inter-craft communication among planners; the productivity dependency network was used as the basis for evaluating inter-craft communication. Due to the similarity of these projects, the generalizability of the correlations should be sufficient. It is also worth noting that the correlation network illustrated in Figure 3 is an undirected network. It is based on a neutral Pearson correlation analysis. The correlation coefficients only show how one craft is affected by another and vice versa, such as how the productivities of concrete pouring and concrete formwork are mutually dependent. It is possible to analyse the direction of dependency based on more in-depth data, such as an analysis of detailed logs and schedules of construction operations. Otherwise, it is beyond the scope of this study and the available data. Meanwhile, we found that at the craft level, the dependency is often mutual. Therefore, an undirected network should serve well in a craft-level analysis.

Experiment design

A total of 103 student subjects were recruited to participate in the human subject experiment. Among them, 47 were graduate students (M.S. Construction Management) and 56 were junior and senior level undergraduate students (B.S. Construction Management). All students had previously completed construction cost estimating courses and had sufficient knowledge about labour hour estimating, productivity and the reference class forecasting method. In addition, prior to the experiments, sessions were held to introduce the procedures and the instruments (Google sheets) of the experiments. As a result, the students qualified for the experiments. The subjects were asked to estimate the total labour hours of a hypothetical power plant project. Since we identified 26 crafts for a power plant project, subjects were assigned into three groups of 26, with each subject estimating the labour hours of a single craft in each round. The subjects were shuffled throughout the experiment to make sure that each individual estimated a new craft each time. The participation results were translated into bonus points on final exams and the subjects were not compensated.

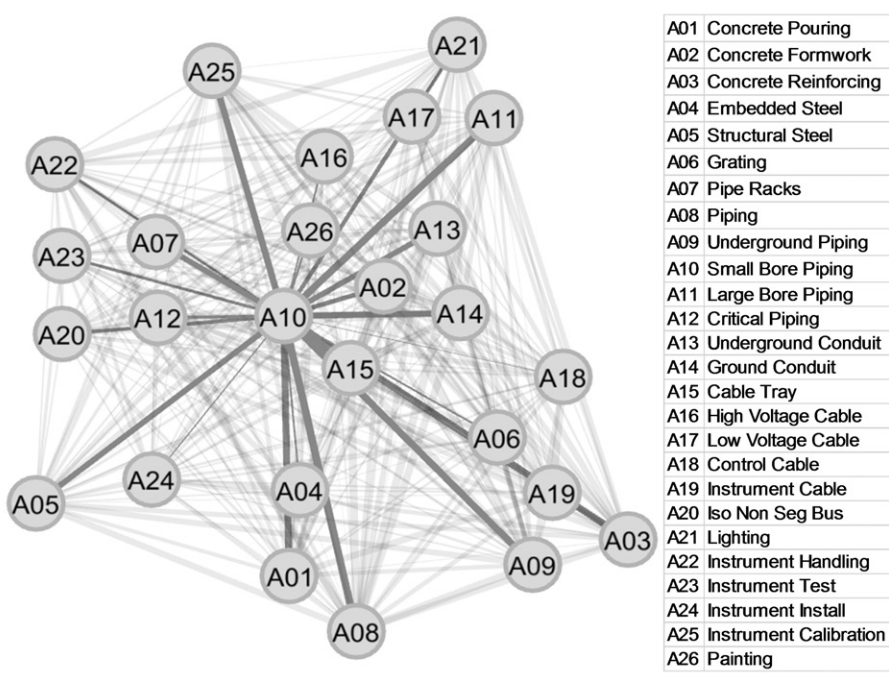

Figure 3. A weighted network shows the productivity relationship of 26 major crafts in 38 capital projects. A thicker edge refers to a stronger inter-craft correlation in productivity.

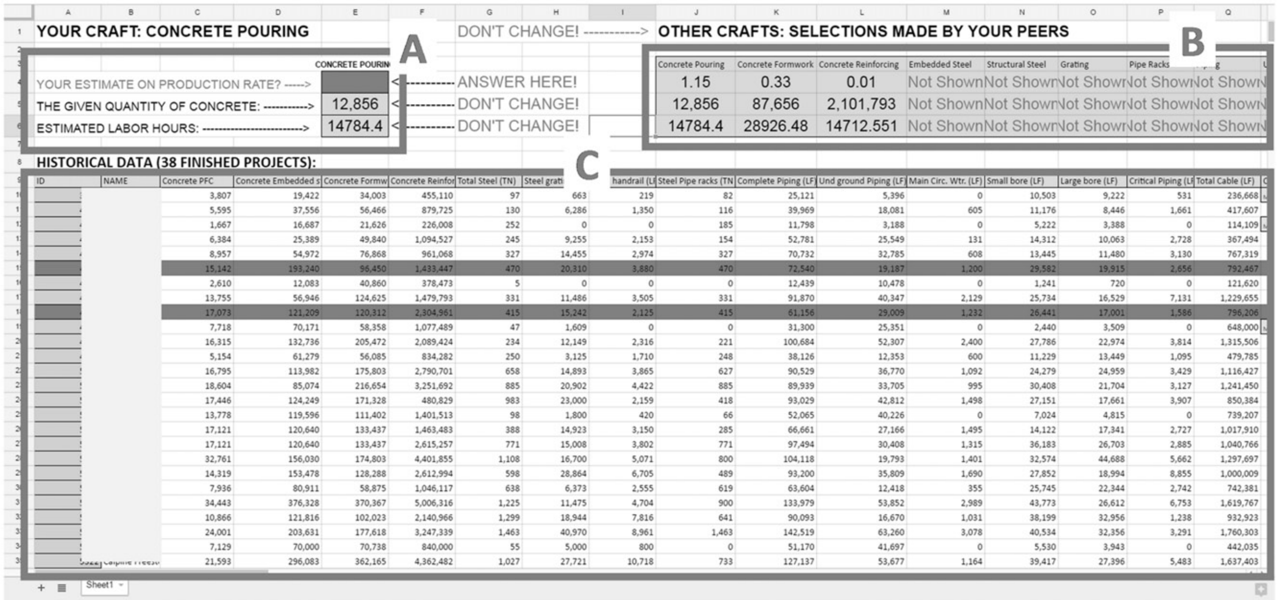

Figure 4. User interface in the experiment. Zone A: Subjects were asked to enter their estimated production rate here. The quantity of the designated craft was based on the estimated production rate; labour hours were calculated automatically. Zone B: According to the network topology under test, subjects were able to see estimates made by certain peers in Zone B. Zone C: Subjects were able to see the quantity and production rate information of all 26 crafts of 38 finished projects.

Each subject was provided with a unique Google sheet to submit their estimates, as illustrated in Figure 4. In each round of the experiment, the subjects were asked to fill out the *estimated production rate* of the designated craft, which was used as the basis for the *labour hour* calculation:

$$\text{labour hours} = \text{quantity} \times \text{estimated production rate} \tag{1}$$

In accordance with the *reference class forecasting* method, Google sheets containing the quantity and historical production rate information of all 26 crafts based on the 38 finished power plant projects were provided to the subjects (Figure 4). Each subject, depending on the role he/she was playing, received a Google sheet where the subject needed to enter his/her estimated production rate. According to the predetermined communication network topology, subjects could also see the estimates made by certain other peers. All experiments were performed and completed during class time, which was about one hour. Eventually, individual estimates were aggregated to calculate the total estimate.

We created a real-time communication system with the Google sheets. First, we used a Google Application programming interface (API) to automatically generate 26 Google sheets (each represents a craft). Then, in Zone B, we used a Google sheet function IMPORTRANGE to update cells in real time. If two subjects were connected, both of them would be able to see each other's estimates in real time. This allowed them to dynamically change their own estimate based on information received from peers. We prepared a short video about this process: https://www.youtube.com/watch?v=z0eoDUWv4Pg.

In order to evaluate the degree of collective optimism bias, we performed a Monte Carlo simulation to establish the reference line (that was treated as the realistic estimate). The craft production rates of the 38 finished power plant projects were used as random number generators to determine the statistically expected labour hours of the tested hypothetical project. Monte Carlo simulation was used to generate the most statistically sound estimate based on the distributions of historical data. The simulated estimate was then used to benchmark the estimates given by human subjects. We did not use the simple calculation of the median values to represent the expect values because many of the production rate distributions were not symmetric. In this case, cost $= quantity* production rate cannot be obtained by using the median values of the data. The following steps were taken to perform the Monte Carlo simulation:

1. Collect the quantity data of 38 completed projects at the craft level (26 crafts);
2. Retrieve information about total labour hours for each of the 26 crafts in every project;
3. Calculate the production rate as labour hours/quantity;

4. Fit probability density functions (PDFs) for each of the 26 crafts; in this study, we did not predefine the PDFs of the craft production rates; instead, we applied the Akaike Information Criterion (AIC) test to evaluate the fitness of different PDFs and allowed the data to speak for itself. The AIC is a statistical estimator of the relative quality of PDFs for a given set of data (Bozdogan 1987). Given a collection of possible PDFs for the data, AIC can estimate the quality of each PDF, relative to each of the other PDFs, and thus provides a means for PDF selection (Bozdogan 1987). Compared to the predefined PDFs, AIC can select the PDFs that best describe the data. The AICs instead of predefined PDFs were used because the AIC-fitted PDFs could improve the accuracy of the following Monte Carlo simulation.
5. Obtain the craft level quantity data of the sample project for the experiment;
6. Use the fitted PDFs of the 26 crafts as random number generators (RNGs) to sample production rate in each simulation trial;
7. Simulate the expected labour hours for each of the 26 crafts of the sample project as: simulated production rate* craft quantity;
8. Simulate the total labour hours for each simulation trial by summing up simulated labour hours of all 26 crafts;
9. Repeat the simulation 2000 times;
10. Fit the distribution of total labour hours and use the mean value as the simulated reference line. Because the total cost is an aggregation of the quantities and production rates of 26 crafts, according to the Central Limit Theorem (Rosenblatt 1956), the total cost estimate will ultimately follow a normal distribution, where the mean value is equal to the median value.

The Monte Carlo simulation used in our experiment only refers to a cost simulation instead of schedule simulation. In other words, we were interested in knowing the aggregated labour hours as a result of varying production rates, rather than as a result of construction processes. The result, *1,326,894 hours*, was deemed to be the reference line that reflected the most realistic estimate (statistically). If the subjects gave an estimate lower than this number, then they were relatively optimistic about productivity (thus requiring fewer labour hours); otherwise, they tended to be relatively realistic or pessimistic about productivity (thus requiring more labour hours). To account for the uncertainties, we used a range ($80\% \times 1{,}326{,}894$ – $120\% \times 1{,}326{,}894$), instead of a deterministic line, to differentiate optimism and pessimism. The subjects' performance was eventually evaluated based on how close their total estimate was to the reference line. The ranked order of their performance was eventually translated into bonus points on their final exam.

We examined the estimates given by the subjects under four different communication network topologies, as illustrated in Figure 5. The first one, distributed, required the subjects to make their estimates independently; in other words, they could not see the estimates made by others. The opposite is the full connection network, where subjects could see the estimates made by all others. Based on the correlation coefficients (ρ) among the 26 crafts, we also designed two additional networks, namely "0.5 Cord" ($\rho > 0.5$) and "0.4 Chord" ($\rho > 0.4$). Data from the 38 finished projects show correlations among the production rates of the 26 crafts, but at different levels. For example,

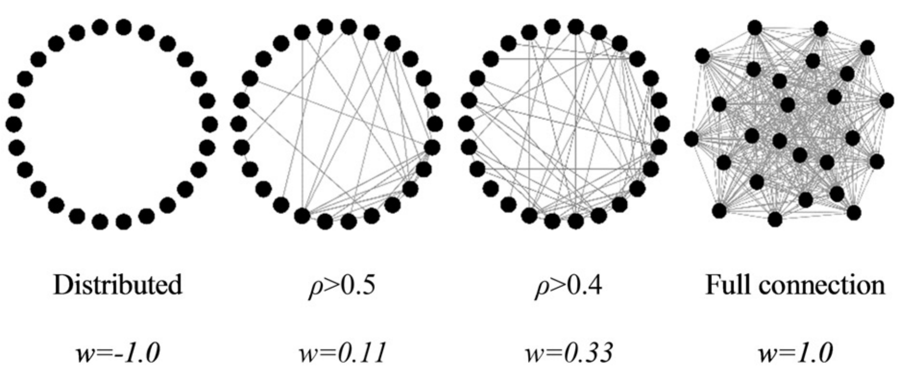

Figure 5. Different network topologies tested in the hypothetical project estimating game (node =26). Each node represents a student in the experiment. ρ is the correlation coefficient between the production rates of two nodes based on historical data. w is small-worldness indicator proposed by (Telesford *et al.* 2011). w = 0 means that the network is a small-world network, a mixture of local connectivity with long distance connectivity.

the correlation coefficient between the production rates of "A10 small bore piping" and "A15 cable tray" is 0.787, while it is only 0.008 between "A04 embedded steel" and "A07 pipe racks". We assume that the correlation coefficient between two crafts corresponds to the communication needs of the two subjects: if the correlation between two crafts is stronger, their production rates are more interdependent. The *0.5 Chord* network means that two students could see each other's estimates only if the correlation coefficient between the two corresponding crafts was greater than 0.5. Requirements were similar for the *0.4 Chord* network. One of the limitations of this study is the difficulty of testing all possible communication networks, continuously ranging from no commutation to full communication. We can only select the most representative network topologies in this exploratory study to answer the basic question: Can communication network topology affect the decision bias? We selected *0.4 Chord* and *0.5 Chord* for two reasons: First, literature (Rosenkrantz *et al.* 2013) suggests that $\rho = 0.4–0.6$ usually refers to a moderate correlation, which is a focus in this study. Second, if we select 0.7 as the correlation coefficient threshold, there would be only one connection existing between "Piping – 365 FF&E Small Bore Combined Cycle WHR" and "Electrical – Cable Tray – Combined Cycle WHR" ($\rho = 0.786$). In order to test the representative networks, especially the ones that represent the moderate level of communication need, we selected *0.4 Chord* and *0.5 Chord*. Eventually, experiments under each network topology were repeated 12 times for statistical analysis.

It is worth noting that the communication needs in the planning phase between two craft estimators does not necessarily mean the dependency in construction operations. For example, in our case, "A10 Small Bore Piping" and "A15 Cable Tray" show a very strong correlation in their production rates based on the historical data, but in construction they are two independent activities – done by two independent crafts/ subcontractors (piping craft and mechanical craft), with no obvious dependency in construction operations (such as one relies on another). The main reason of their correlation in production rate is because both of them are affected by the overall complexity of the power plant design – a plant with a more complex design often means slower piping and cabling progress, because of the special installation requirements and usually a more complex spatial configuration. As a result, there is still a natural need for the estimators of these two crafts to coordinate and cross check their estimates in the planning phase, although these two crafts seem to be independent in construction. We found that compared to the construction dependency, the production rate correlation shown in the historical data is a better indicator of the communication need. In other words, if the historical data shows a correlation between two crafts, it may be natural for the two estimators to cross check their numbers. In fact, it is a common practice in project planning. The need for estimators of two correlated crafts to communicate is more about a planning practice (i.e., the need for cross-checking) than about dependency during construction.

It is also worth noting that we did not use randomly generated networks as most similar studies have done (Kearns *et al.* 2006). Modelling the communication network should build on the fact that there is a need for communication between two estimators. The most reasonable base for this study is the correlation of productivity. The existence of a correlation between two crafts in productivity, in spite of the causes, often encourages cross-checking behaviours of the two estimators in the planning phase. As a result, we used the craft productivity correlation network as the base for modelling different communication networks, but we also recognize that the driving factors for communications in real projects can be more complex, and thus the approach we used is not intended to make any practical recommendations.

Experiment results

Our results show that more than 79% of the total estimates given by the subjects were lower than the reference line, *1,326,894* hours. Table 2 lists the estimates given by the subjects in 12 trials of the experiment. Table 3 lists the descriptive statistics of the estimating results of different communication network groups.

The results indicate that the subjects demonstrated a collective optimism bias most of the time (lower

Table 2. Estimates (labour hours) given by the subjects (simulation result =1,326,894).

Trials	Distributed	0.5 Chord	0.4 Chord	Full connection
1	1,115,186.94	1,447,240.88	915,772.19	1,497,979.71
2	909,839.71	1,057,314.25	1,428,797.92	1,134,947.17
3	1,113,320.86	1,431,261.52	1,072,366.35	989,669.99
4	1,210,862.90	1,196,769.93	847,965.25	754,409.00
5	1,019,745.31	1,302,079.08	778,266.12	1,006,907.69
6	1,198,846.17	1,328,249.82	1,131,722.64	882,303.94
7	1,064,940.79	1,537,441.54	1,384,848.64	625,415.55
8	1,030,145.10	1,289,586.32	1,370,900.20	892,478.03
9	1,042,580.53	1,244,483.58	1,290,359.98	829,261.22
10	1,024,334.11	1,228,804.75	1,396,622.71	884,949.56
11	969,195.66	1,196,919.71	1,292,354.61	774,212.07
12	1,020,526.41	1,326,912.23	1,290,449.54	828,365.87

than 80% × 1,326,894). This systematic tendency of optimism supports empirical data in prior studies (Flyvbjerg *et al*. 2003).

We then examined whether the degree of collective optimism bias varies under different communication network topologies. As illustrated in Figure 6, the subjects tended to give more conservative estimates (i.e. greater than the reference line – realistic estimate) under the *0.5 Chord* communication network, and seemed to be more optimistic (i.e. lower than the reference line – realistic estimate) under the *Full Connection* network.

Then, we performed a pairwise Wilcoxon signed-rank test (Woolson 2008) to evaluate whether the levels of optimism bias were different under different tested communication network topologies. The Wilcoxon signed-rank test is a non-parametric statistical hypothesis test used to compare whether the population mean ranks differ across two groups (i.e. it is a paired difference test) (Woolson 2008). It is an alterative method for the Analysis of Variance (ANOVA) when the samples do not follow the normality assumption. Table 4 lists differences between certain pairs of topologies. The results indicate significant differences on the optimism bias level between certain groups ($p < 0.05$), including *0.5 Chord* versus *Distributed*, *0.5 Chord* versus *Full Connection*, *Full Connection* versus *Distributed,* and *0.4 Chord* versus *Full Connection*. We also performed a Kruskal–Wallis test (Kruskal and Wallis 1952), a non-parametric method for testing whether samples originate from the same distribution. It is often used for comparing two or more independent samples of equal or different sample sizes when the samples do not follow the normality assumption. The result shows that the estimating results of all four commnucation network groups are from different distributions ($p = 0.0002 < 0.05$). It also supports that human communication topolgy can affect the group level optimism bias. Therefore, the central hypothesis is supported.

We were also interested in quantifying the influence of network topology on optimism bias. Figure 7 indicates a nonlinear relationship between the small-worldness of the network and optimism bias (measured by the percent difference between the estimates given by the students and the reference line – realistic estimates). In other words, too much or no communication may both lead to biased estimates. It suggests that there is certain under explored communication mechanism that affects the group decision in capital project planning. The possible interpretation of the result is: over-communication and insufficient communication both lead to biased group decisions. There shall be an optimal level of communication in practice.

Table 3. Descriptive statistics of the estimating results of different communication network groups.

Group	N	Mean	Median	Std Dev	Lower CL	Upper CL
Distributed	12	1059960.4	1036362.8	87588.8	1004309	1115612
0.5 Chord	12	1298922	1295832.7	129768	1216471	1381373
0.4 Chord	12	1183368.8	1290404.7	229519	1037540	1329198
Full connection	12	925074.9	883626.7	223170	783279.6	1066870

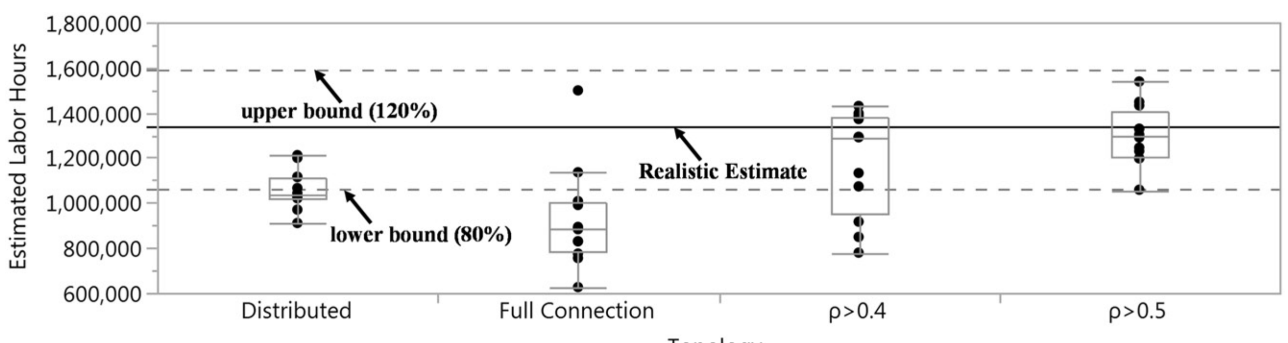

Figure 6. Communication network topology significantly affected the collective optimism bias in the human-subject experiment.

Table 4. Pairwise Wilcoxon test results, cross group difference.

Group A	Group B	Score mean difference	Std Err Dif	p-Value	Lower CL	Upper CL
0.5 Chord	Distributed	10.4167	2.887	0.0003*	131979	332054
0.5 Chord	Full connection	9.9167	2.887	0.0006*	282679	546312
Full connection	Distributed	−7.5833	2.887	0.0086*	−284060	−35673
0.4 Chord	Full connection	6.75	2.887	0.0194*	30823	502545
0.4 Chord	Distributed	5.0833	2.887	0.0783	−67124	319908
0.5 Chord	0.4 Chord	2.5833	2.887	0.3708	−82770	299539

*$p < 0.05$.

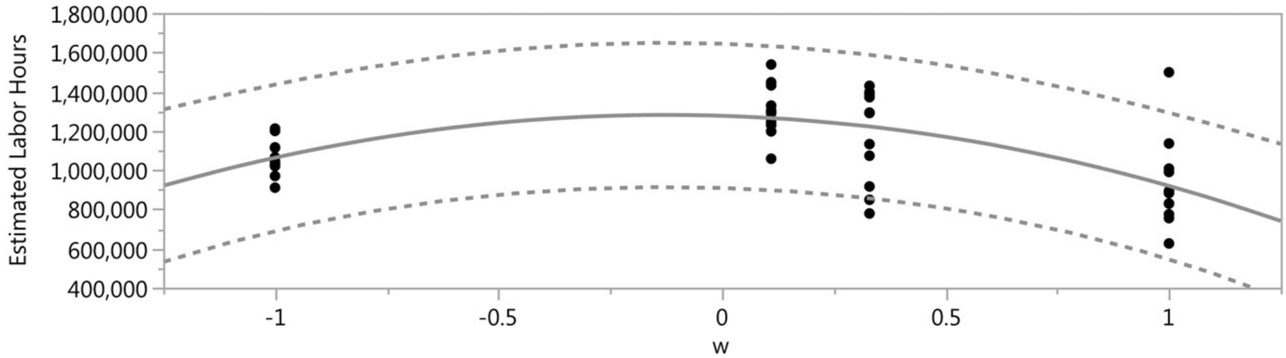

Figure 7. Relationship between small-worldness (measured by w) and level of optimism bias (measured by delta%). Result shows there is a two order relationship between w and delta% – it suggests a nonlinear relationship between small-worldness (measured by w) and optimism bias.

Similar phenomenon has been discovered by a study published in *Science*. In a map coloring experiment, Kearns *et al*. (2006) found that increasing communications among teammates improved the group decisions at the very beginning, but soon negatively affected the group decision beyond certain point. They concluded that "*providing more information can have opposite effects on performance, depending on network structure*" (Kearns *et al*. 2006). Our study tests this phenomeno1n in the context of optimism bias in capital project planning. It is unclear why, in our experiment, something in the middle led to a relatively realistic estimate, clearly deserving further investigation.

We used a small-world measure w to quantify the tested topologies (Telesford *et al*. 2011). Small-world networks are networks where most nodes are not neighbours, but can be reached from every other node by a small number of hops (Watts and Strogatz 1998). It is an emergent property of many natural networks such as social networks (Amaral *et al*. 2000). In the literature (Telesford *et al*. 2011), small-worldness of a network can be measured by the following equation:

$$w = (L_{rand}/L) - (C/C_{latt}) \tag{2}$$

where L is the path length of the network, a measure of the distance between nodes in the network, calculated as the mean of the shortest geodesic distances between all possible node pairs:

$$L = \frac{1}{N(N-1)} \sum\nolimits_{ifn,i \neq j} d_{ij} \tag{3}$$

where d_{ij} is the shortest geodesic distance between nodes i and j. C is the modularity or clustering coefficient, i.e. the proportion of edges e_i that exists between the neighbours of a particular node (i) relative to the total number of possible edges between neighbours (Bullmore and Sporns 2009). The equation for C at an individual node of degree k_i is:

$$C_i = \frac{2e_i}{k_i(k_i - 1)} \tag{4}$$

The small-world measurement, w, is defined by comparing the modularity of the network to that of an equivalent lattice network, C_{latt}, and comparing path length to that of an equivalent random network, L_{rand}. Values close to zero are considered small world, because a small-world network should reflect $L \asymp L_{rand}$ and $C \asymp C_{latt}$. Positive values indicate a graph with more random characteristics, while negative values indicate a graph with more regular or lattice-like characteristics.

Discussion

Our study aims to investigate the group-level optimism bias, instead of individual-level optimism bias, observed in capital project planning. Evidence shows that even each individual estimator could have given realistic estimates to the best knowledge, when a group of estimators work together, the final estimate at the group level can still be overly optimistic. There is an under explored mechanism that translates individual decisions to deviated group decisions, which is potentially more complex than the instructions or decisions given by the top managers. The social psychology literature has investigated this individual-group transition and proposed certain theories to explain the gap. One explanation is the shared mental models, i.e. the tendency of a person to be influenced by others and change his/her original judgement in interactive group discussion (Mohammed *et al*. 2010). Another theory pertains to the psychological safety (Edmondson 1999), i.e. the phenomenon that a person feels more comfortable when he/she is echoing the opinions of other team members. Under the wrong conditions, group discussion can have negative effects

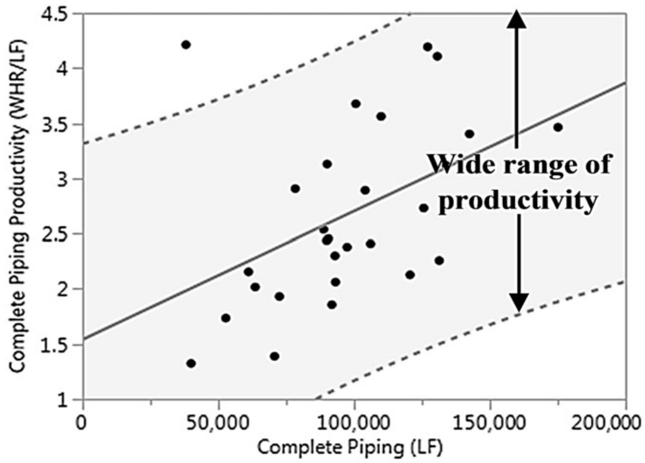

Figure 8. Projects with similar complete piping work still show a wide distribution of production rate. For example, when a project requires 100,000 LF (linear foot) piping, its production rate could range from 1.1 hour/LF to 4.0 hour/LF, based on our database of 38 finished projects. Optimism bias still applies.

on decision quality. Group interaction can accentuate common misconceptions (Hinsz *et al.* 1997). It may also result in group polarization, a phenomenon in which members' initial preferences are amplified. For example, if members individually are generally optimistic (Lovallo and Kahneman (2003) suggested), group discussion would make them more optimistic and thus result in even more overly aggressive estimates.

Two interesting observations in our experiment deserve further exploration. First, our findings highlight the importance of showing the assumptions and considerations previous estimators held when making estimating decisions in the reference class forecasting process, in addition to the historical information of previous projects. The reference class forecasting method requires decision-makers to identify a similar project and use the estimates of the similar project as the baseline for new estimates. Literature suggests that providing information about similar projects will help control optimism bias when making predictions on the present project (Flyvbjerg 2007, 2008). However, it should be noted that due to the technical uncertainty of capital projects, it may be difficult for decision-makers to evaluate the similarity between two projects. For example, as illustrated in Figure 8, for *complete piping*, even when projects are of similar magnitude (LF – linear footage), the production rate could vary by more than 300%. In our experiment, this means that even though the students could find a similar historical project from the historical database (Figure 4, Zone C), they still need to pick a number from a wide distribution (Figure 8). Moreover, our previous work also found that even when more parameters were introduced (e.g. job site configuration), the similarity between two projects was still extremely difficult to measure, probably due to the vast search space (Du and Bormann 2014). As a result, the main assumptions and considerations pertaining the selection of similar projects should be incorporated in the reference class forecasting process as they indicate the dimensions of similarity measurement (Flyvbjerg 2008).

The second observation is that we need to rethink about the role of communication in controlling the quality of cost estimating. Our experiment showed that moderate communication ($\rho > 0.5$ communication network) led to more realistic estimates than intensive communication (*Full Connection* network, i.e. everybody can see everybody else's selection) (Figure 6), and *Full Connection* network was always leading to more aggressive estimates. This contradicts many studies advocating a linear relationship between decision quality and level of communication in construction (Ballard and Howell 1994). We further propose that it is due to certain inherent cognitive processes pertaining to optimism bias. A recent study has shown that people update their beliefs more in response to information that is better than expected compared to information that is worse (Sharot *et al.* 2011). In other words, in a communication between a relatively optimistic individual and a relatively pessimistic individual, the latter tends to substantially change his/her judgement based on the optimistic information received from the other, while the optimistic individual may insist on his/her original judgement. Compared to pessimism, optimism is easier to spread in communication networks, like a virus (Figure 9). Neural science literature reveals the neural basis for this phenomenon: distinct regions of the prefrontal cortex track estimation

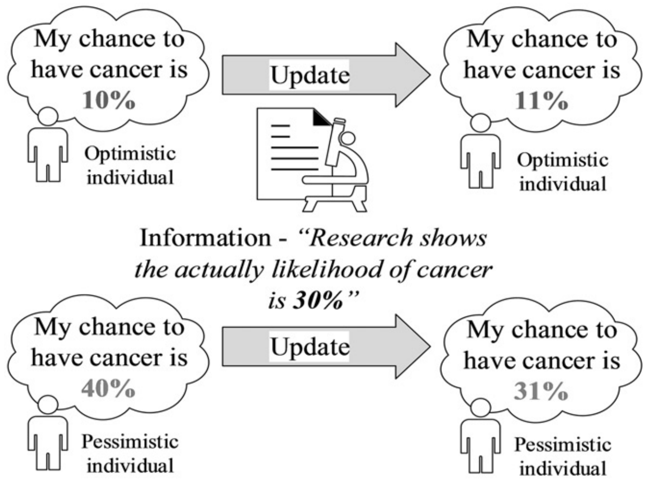

Figure 9. People are more sensitive to information that is better than expected (Sharot *et al*. 2011). As a result, optimism (like a virus) spreads easier than pessimism in a communication network.

errors when they call for a positive update, both in highly optimistic and less optimistic individuals. However, highly optimistic individuals exhibit reduced tracking of estimation errors that call for negative updates within right inferior prefrontal gyrus (Sharot *et al*. 2007). Our experiment further revealed that a network closer to small-world status may help control the collective optimism basis, but the mechanism is unclear. This deserves further investigation because understanding the reason why network topologies, such as small-worldness, lead to controlled optimism bias will set a stepping stone for optimizing communication networks.

It is worth noting that the test subjects in this experiment were students, who may not have a similar level of experience and knowledge as that of professional estimators. Therefore, we made certain arrangements so that students would make estimates based on good reasoning. During the experiments, the students were provided with the complete dataset of all 38 projects, and were asked to make their estimates based on the historical data. It was found that the students did not just give random estimates. Instead, they carefully checked the historical 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 exams. 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 shortest time estimates. In addition, prior to each experiment, the rationale and procedure of reference class forecasting were introduced. We used these experiment 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 judgements. Otherwise, our objective was to understand the fundamentals about the impacts of communication network topologies on estimating bias. If we can reveal that the variance of estimates can be attributed to the variance of communication networks, then our study would be a contribution to the discipline and it deserves further investigation, especially with professional estimators.

There are many secondary factors affecting the group optimism bias. In our experiment, we managed to control the secondary factors and only focused on the communication network topology. All the subjects were randomly assigned to each group. For each experiment trial, the subjects were randomly shuffled and asked to estimate the cost of a different craft. Each subject was only asked to review 38 data points in each trail. The tasks were also made very clear: estimate the cost of the assigned craft by reviewing the historical data points and others' estimates (if available). Other background information was limited to reduce the influence on their judgements. The random assignment and relatively simple judgement task will help reduce the impacts of optimism-related decision heuristics such as anchoring, availability and representativeness. Even if the subjects held individually different decision heuristics, because they were shuffled in different experiment trails and the results were aggregated to study the overall pattern, the difference should have been cancelled out.

Conclusions

Capital projects are critical to our economy. However, evidence shows that the efficiency of these projects are affected by inaccurate, mainly optimistic, planning decisions. The optimism bias, i.e. people's inclination to be overly optimistic about the chance of success, has been found to be a major contributor of aggressive budgets and plans in many capital projects, which has led to inefficient allocation of scarce public resources and common time and cost overruns. The literature has attempted to understand and mitigate optimism bias of key decision makers from the individual and psychological perspective, yet how individual optimism is aggregated and translated into optimistic plans at the group level is poorly understood.

This article hypothesizes that human communication network topology, i.e. patterns of contact created by the flow of messages among decision-makers, can significantly affect the level of optimism bias at the group level. Using a series of human subject experiments, this study tested the group estimates under four different communication network topologies, namely *Distributed*, *0.4 Chord*, *0.5 Chord* and *Full Connection*. The experiments, using real project data, supported our central hypothesis.

The findings of this study are expected to advance our knowledge about the role of human communication networks in controlling optimism bias at the group level in project related decision-making. The empirical data collected in this research will add to the literature's direct evidence of correlations between human communication network topologies and degree of collective optimism bias. The exploratory simulation experiments will help unveil the transition mechanism from a well-understood individual cognitive bias to harmful collective optimism via a poorly understood group process, observed in most capital project organizations. This study aims to extend the horizon of decision bias literature from a focus on controlling bias at the individual level to a more holistic structure-driven theory. Beyond communication and optimism bias, this research is expected to provide a theoretical foundation for exploring the role of other intra- or inter-organizational networks in transforming a variety of individual decision biases into an unexpected group decision.

This study also contributes to group polarization theory in project related decision-making, i.e. tendency for a group to make decisions that are more extreme than the initial inclination of its members. The findings add evidence about conditions and processes leading to a systematic shift to one extreme end, rather than another. It heeds the call to explore new directions in risk analysis and management of capital projects, but it also has the potential to improve decision-making quality in other areas challenged by uncertainties. The findings of this research will provide a usable theoretical basis and methodology to facilitate the development of simple, yet effective, decision support systems to reduce bias that occurs during decision-making in capital project planning. It may also assist policy makers in reasonably allocating public resources and reducing waste.

Proving the impacts of human communication network topology on group decision bias is also of importance to the industry practices. In real world, the team structure of a capital project is usually driven by the contractual requirements or the customs. Little has been done to examine a scientific process of organizing the organization, in terms of improving group decision quality. Evidence in organizational science literature has shown the relevance of organizational structure in group decision quality, efficiency and effectiveness, such as (Kearns *et al*. 2006), but the findings should be interpreted in the construction context to have real impacts in the industry. Although still in its infancy, this study constitutes the stepping stone for future investigation into the group decision mechanism driven organizational design for capital projects.

One of the limitations of this study is the limited sample size. To draw any sound statistical conclusion, the sample size should be sufficient to satisfy certain assumptions. As a result, one of the future agenda items is to expand the experiments to include more subjects. We expect to generate enough data points to better understand the nonlinear relationship between communication network topology and group level optimism bias in capital project planning. In addition, we expect to test the influence of secondary factors, such like different decision heuristics and demographic factors, in the formation of optimism bias in our future work. The ultimate goal of this research is to develop a model that helps predict group decision bias and guides the organizational design in capital project management.

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