LOGIT MODELS FOR EARLY WARNING OF DISTRESSED CAPITAL PROJECTS

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Abstract. The focus of this study is to demonstrate how probabilistic models may be employed to provide early warnings for distressed capital projects. While identifying the key determinants of project performance is important, few studies test discriminatory power of variables for predicting distressed capital projects. Thus, this longitudinal study of 121 capital projects identifies key variables in the initiation and planning phases of projects that differentiate between healthy and distressed projects at completion. Subsequent univariate logistic analysis shows that the *Quality* variable provides the highest univariate classification accuracy. Hierarchical logistic-regression analysis reveals high classification accuracy and relatively small differences in overall classification rates. Out-of-sample forecasting validation demonstrates that the optimal model provides a reasonably good overall classification rate of 85.37%. Ultimately, our findings suggest that it is feasible to discriminate simultaneously between healthy and distressed projects prior to the project execution phase in the capital facility delivery process, providing an early warning of projects in distress.

Keywords: capital projects, distressed projects, early warning signs, performance assessment, logit analysis, longitudinal study.

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Introduction

A central tenet of the study of project management is to identify the critical determinants of project performance. Of course, extensive research in the project management field examines and identifies a wide variety of measures that describe project performance and the inputs that affect the performance. Some studies emphasize the importance of the execution phase on project performance and identify the critical factors associated with the execution phase (e.g., Chen *et al.* 2010; Hoegl, Parboteeah 2007; Keller 1986, 1992, 1994; Tabassi, Bakar 2009). Others suggest examining and identifying the critical factors of project performance on the basis of the overall project life cycle (e.g., El-

Sayegh 2008; Ibbs *et al.* 2001; Ling *et al.* 2009; Oke, Idiagbon-Oke 2010; Scott-Young, Samson 2008; Zou *et al.* 2007).

However, despite the panoply of studies into which factors affect project performance (e.g., Chen *et al.* 2010; El-Sayegh 2008; Oke, Idiagbon-Oke 2010; Schieg 2007; Scott-Young, Samson 2008), few longitudinally test discriminatory power of variables in the early stage of the project delivery process for differentiating between healthy and distressed capital projects at completion. The capital projects industry includes both the delivery and the maintenance of facilities such as commercial and institutional, industrial, and residential buildings. Our focus is on the delivery process of capital projects, e.g., from the initiating to closing phases of projects. Thus, there appears to be a lack of studies that provide early warning models for predicting distressed capital projects. The study of early warning models is important because it enables management to intervene early into the affairs of problem projects so that corrective actions can be taken before it is too late.

The first objective of this study, therefore, is to conduct a longitudinal experiment that examines discriminatory power of variables associated with the project-initiation and planning phases on capital project outcomes – those variables not in the project execution phase or the overall project life cycle, but rather, specifically in the project-initiation and planning phases. One of the obvious benefits of such an experiment design is that it warns managers of distressed projects *before* the execution phase in the capital project delivery process. The second objective is to assess, through multivariate logit model-building and validation, how well the variables detect healthy and distressed capital projects.

The rest of the paper is organized as follows. "Research Background" reviews related studies, "Hypotheses" delineates the test hypotheses, "Research Methods" presents the research methodology and describes the sample collection, and "Results" depicts the statistical tests, model-building, and validation. "Discussion" discusses the implications of the research results. "Conclusion" presents the research summary and conclusions.

1. Research Background

A central tenet of the study of project performance is that identifying specific impacts on project performance will guide project managers to engineer critical issues scientifically during project execution. Not surprisingly, researchers and professional associations (e.g., Anand *et al.* 2010; Brown *et al.* 1990; Cao, Hoffman 2011; El-Mashaleh *et al.* 2010; Ghosh, Skibniewski 2010; Hoang, Rothaermel 2005; Hsu *et al.* 2011; Keller 1986; Ling *et al.* 2009; Project Management Institute 2008; Qureshi *et al.* 2009; Zeng *et al.* 2009) conduct extensive studies to examine and identify these key determinants of project performance.

For example, Keller (1986) examines 32 project groups in a large R&D organization using a longitudinal design based on hierarchical regression analysis and concludes that group cohesiveness, physical distance, job satisfaction, and innovative orientation are factors in project performance. Brown *et al.* (1990) assess 14 project teams that

worked on the same complex, computer-simulated project using ANOVA and regression analysis; they conclude that group harmony significantly influences the performance of a project.

Additionally, Keller (1992) evaluates 66 project groups in three industrial R&D organizations using a longitudinal experiment based on factor analysis and regression analysis. He concludes that transformational leadership, which is the sum of charismatic leadership and intellectual stimulation, significantly affects the performance of projects. Using the data from 98 project groups in four industrial R&D organizations, Keller (1994) further tests the hypothesis that a fit between the task technology's characteristics and information-process needs predicts project performance. Concurrent and one-year-later management ratings of project quality, based on absolute-difference scores as a measure of fit, support the hypothesis.

Subsequent work by Hoegl and Gemuenden (2001) and Hoegl *et al.* (2003) uses regression analysis to examine the effects of teamwork quality on project performance. Based on data from 145 projects in four software development organizations, they conclude that teamwork quality is associated with the performance of projects posing high task innovativeness. Further, Hoang and Rothaermel (2005) use binary logistic analysis to examine the success of 158 joint R&D projects in 43 pharmaceutical firms; they claim that the general alliance experience of biotechnology partners, but not of pharmaceutical firms, positively affects joint project outcomes.

Song *et al.* (2007) conclude that initial planning conditions and the effectiveness of front-end planning management affect how well R&D plans and the later R&D process perform based on two R&D projects. Similarly, Schwab and Anne (2008) examine 239 U.S. movie projects from 1931 to 1940 and determine, using regression analysis, that project performance depends on the perceived relevance of prior performance and on organizational control over project participants.

Using data from 56 capital projects in 15 process-industry companies, Scott-Young and Samson (2008) examine the impact of organizational context, team design, team leadership, and team process factors on project performance using factor analysis and regression analysis. Their test results show that these factors are significant determinants of project outcomes. More recently, Hoang and Rothaermel (2010) examine 412 R&D projects in 43 pharmaceutical companies from 1980 to 2000 and conclude, using a competing risk event history model, that alliance exploitation experience positively affects R&D project performance. They also show that when firms combine internal exploitation experience with external exploration experience, the negative effects on R&D project performance occur and are more significant.

Recently, Anand *et al.* (2010) analyze 98 projects in five companies using hierarchical regression. They show that the inclusion of softer, people-oriented practices for capturing tacit knowledge explains a significant amount of variance in project outcomes. Shepherd *et al.* (2011) use hierarchical regression analysis to examine the effects of negative emotions and affective commitment resulted from project failure on subsequent project performance. Based on data from 257 research scientists about project teams in

12 different research institutes in Germany, they conclude that emotions as outcomes may influence emotions as inputs for subsequent projects; that is, the negative emotions of project failure create an affective commitment to the organization.

More recently, Calamel *et al.* (2012) examine two collaborative R&D projects in a large global innovation cluster in France using a longitudinal design based on in-depth case research. They conclude that team collaboration, a product of social construction fostered by managerial support, is important factor in project performance.

Although many studies use a wide variety of measures to describe project performance and the input characteristics that affect the performance (e.g., Anand *et al.* 2010; Dumont *et al.* 1997; Hoegl *et al.* 2003; Ibbs *et al.* 2001; Oke, Idiagbon-Oke 2010; Song *et al.* 2007; Sperpell 1999), most studies emphasize the project-execution phase (e.g., Chen *et al.* 2010; Hoegl, Parboteeah 2007; Keller 1986, 1992, 1994; Tabassi, Bakar 2009) or the overall project life cycle (e.g., El-Sayegh 2008; Ibbs *et al.* 2001; Oke, Idiagbon-Oke 2010; Scott-Young, Samson 2008; Zou *et al.* 2007).

Further, most studies identify the critical determinants of project performance using contemporaneous data (e.g., Chen *et al.* 2010; El-Sayegh 2008; Ibbs *et al.* 2001; Ling *et al.* 2009; Oke, Idiagbon-Oke 2010; Scott-Young, Samson 2008; Shepherd *et al.* 2011). Limited studies examine the potential predictors of project performance using longitudinal data.

In particular, although few published studies examine the potential predictors of project performance using longitudinal data, these studies (e.g., Calamel *et al.* 2012; Keller 1986, 1992, 1994) emphasize the project-execution phase and mainly focus on new product development (NPD) and research and development (R&D) – despite the fact that capital projects contribute significant growth to the economy (Chen 2010; Mallick, Mahalik, 2010). As a result, there appears to be a lack of research that longitudinally examines what variables possess a potential discriminatory power to differentiate between healthy and distressed projects prior to the project execution phase in the capital facility delivery process.

2. Hypotheses

The preceding section critiques existing studies of project performance. Now the question is: *What variables in the project-initiation and planning phases can discriminate between healthy and distressed capital projects at completion?*

To answer this question, test hypotheses have to be developed. From an extensive review of the interdisciplinary literature along with consultation with several experienced researchers and practitioners and in an effort to generate a more parsimonious measurement, we choose widely accepted variables that are used to measure the performance of the overall project life cycle for hypothesis tests. These performance variables include *Scope, Quality, Team, Communication, Risk, Change*, and *Innovation*.

Scope. Defining a project's scope is a process by which the project is outlined and prepared for execution (Dumont *et al.* 1997). Whilst a project scope is a detailed for-

mulation of a continuous strategy to be used throughout a project to achieve the project objectives, defining the scope is one of the principal tasks in the project-initiation and planning phases. A poorly defined project scope can experience considerable changes, resulting in cost overruns, delays in the project schedule, rework, disrupted project rhythm, and lower productivity (Dumont *et al.* 1997). Not surprisingly, several studies (e.g., Görög 2011; Kwak, Ibbs 2002; Ling *et al.* 2009; Roman 1964) report that scope management is one of the leading influences on project performance for all project types. Therefore, we form the first hypothesis:

H1: The Scope variable in the project-initiation and planning phases can discriminate between healthy and distressed capital projects at completion.

Quality. High-quality projects create end products that fully meet customer needs, reduce rework of nonconforming tasks, keep customers informed of the progress, and change to meet emerging customer requirements (Tukel, Rom 2001). Thus, whilst quality management starts at the project's initiation, effective quality management ensures the project to meet its requirements in the project delivery process. Naturally, effective quality management has become one of the most frequently studied project performance factors (e.g., Al-Tmeemy *et al.* 2012; Ling *et al.* 2009; Sperpell 1999). Thus, this study proposes that levels of quality performance in the project-initiation and planning phases will be associated with project outcomes at completion. We form the second hypothesis:

H2: The Quality variable in the project-initiation and planning phases can discriminate between healthy and distressed capital projects at completion.

Team. Studies have long recognized team quality as a key factor in overall project performance (e.g., Bendoly, Swink 2007; Brown *et al.* 1990; Keller 1986; Raiden *et al.* 2004; Scott-Young, Samson 2008). Despite the general management literature's increasing interest in team quality, project teams are still under-researched in project management (e.g., Anand *et al.* 2010; Chen *et al.* 2010; Hsu *et al.* 2011; Ling *et al.* 2009; Scott-Young, Samson 2008; Tabassi, Bakar 2009; Thamhain 2009). One recent finding, for example, is that team leadership has significant impact on both the project team and its broader organizational environment, ultimately affecting project performance (Thamhain 2009); another is that the ability to apply and share team knowledge effectively explains a significant amount of variance in project performance (Hsu *et al.* 2011). Thus, we propose the third hypothesis:

H3: The Team variable in the project-initiation and planning phases can discriminate between healthy and distressed capital projects at completion.

Communication. A project involving a number of specialists performing related activities aimed at achieving a predetermined goal requires communication among those specialists (Blankevoort 1984). For over 20 years, research has found that communication quality influences project performance (Clark, Fujimoto 1991; Leonard-Barton, 1995). The reason is clear: communication supports knowledge sharing and hence the performance of projects (Adenfelt 2010; Badir *et al.* 2012; Ochieng, Price 2010). Thus, we propose that levels of communication performance in the project-initiation and planning phases will be associated with project outcomes at completion.

H4: The Communication variable in the project-initiation and planning phases can discriminate between healthy and distressed capital projects at completion.

Risk. Risk is the potential for complications and problems with respect the achievement of a project goal (Cohen, Palmer 2004). Though a recent study of the relationship between risk management and project success did not yield conclusive results (De Bakker *et al.* 2010; Schieg 2006), a general consensus is that effective risk management positively affects the success rate of any project or process in various industries (e.g., Raz *et al.* 2002; Cook 2005; Holzmann, Spiegler 2011; Das, Teng 1999). In particular, the Project Management Institute (PMI) and the Association of Project Management (APM) include risk management as one of the key disciplines of project management. Thus, we propose the fifth hypothesis:

H5: The Risk variable in the project-initiation and planning phases can discriminate between healthy and distressed capital projects at completion.

Change. Change is an unplanned disturbance that typically interferes with the intended progression of project work (Love *et al.* 2002). Changes during a project's development may have significant and often unpredictable effects on the project's organization and management (Ibbs *et al.* 2001; Lehmann 2010; Luu *et al.* 2008). Many time delays, cost overruns, and quality defects can be attributed to changes at various stages of a project (Sun, Meng 2009). Not surprisingly, a project teams' ability to manage change determines project performance to a large extent (Hwang, Low 2012). Hence, we predict that managing change well in the project-initiation and planning phases is associated with superior project outcomes at completion.

H6: The Change variable in the project-initiation and planning phases can discriminate between healthy and distressed capital projects at completion.

Innovation. Innovation often manifests itself in either a new product, service, process, or method (Brady, Söderlund 2008). The relationship between innovation and project management has drawn much research in recent years. Several studies find that better innovation management increases the chances of project success (Chapman, Hyland 2004; Dulaimi *et al.* 2005; Kratzer *et al.* 2006; Oke, Idiagbon-Oke 2010). For example, Beaume *et al.* (2009) conclude a significant interplay between project performance and innovation management based on the comparison analysis of five case studies in the automotive industry. Biedenbach and Müller (2012) show that innovative capability affects innovation output positively, which in return has an impact on short- and long-term project performance, based on data from 18 interviews and 80 surveys with R&D project managers and officers in the pharmaceutical-biotechnology industry. Thus, we propose that levels of innovation performance in the project-initiation and planning phases will be associated with project outcomes at completion.

H7: The Innovation variable in the project-initiation and planning phases can discriminate between healthy and distressed capital projects at completion.

3. Research methods

3.1. Participants and procedures

Of the 500 members of Taiwan's Chinese National Association of General Contractors (CNAGC) that we randomly selected and invited to participate in this research, 121 companies participated – a 24.2% response rate (CNAGC has over 1,000 members). Each of the 121 companies in the sample had assigned a project manager who had just completed the initiation and planning of a capital project scheduled to finish within the next two years. The 121 capital projects fall into three categories: buildings (69 projects composed of 21 commercial buildings, 39 residential buildings, and nine public buildings), transportation facilities (22 projects composed of 15 roadway construction and seven bridge construction), and industrial facilities (30 projects composed of 21 industrial buildings and nine utility systems). Project managers average between one and 26 years of experience; 30 participants had fewer than five years of experience; 51 had between five and 10 years; 33 had between 10 and 20 years; and seven participants had over 20 years of experience. Table 1 provides the sample characteristics.

Surveys collected the data. Prior to the data collection, several experienced researchers and a panel of experts from CNAGC critiqued the questionnaire for structure, readability, clarity, and completeness. These researchers and experts also appraised the extent to which the indicators sufficiently addressed the subject area (Dillman 1978). Based on the feedback from these researchers and experts, the survey instrument was then modified to strengthen its validity.

The final version of the survey questionnaire comprises two sections. The first section, composed of open-ended questions, gathers detailed background information, such as annual revenue, project types, project cost including contract price, budget, contract price for project change, and actual cost, and the project schedule including the contract schedule, scheduled time, contract schedule for project change, and actual schedule.

The second section gathers data for the project variables and is measured by scales based on a synthesis of literature from the project management, group effectiveness, organizational theory, and innovation management fields. Section two consists of multiple-choice questions in which respondents indicate on a 10-point scale the extent to which certain project variables likely affected the project outcomes. Because of space limitations, complete survey questionnaires are not presented here but are available from the authors on request.

Data collection occurred in two stages. In the first stage, participants respond immediately after the end of a project's initiation and planning stages to the portion of the questionnaire that excludes questions regarding project actual cost, project actual schedule, contract price and schedule for project change, and actual cost and schedule for project change. In the second stage, participants respond right after the close of the capital project to the questions excluded in stage one.

Table 1. Sample characteristics

Variables	Value
Responses	
Organizations invited to participate in the research	500
Organizations participating	121
Participation rate (%)	24.2
Annual net revenue of organizations (in US$ millions)	
Less than 5	24
5–15	30
15–25	37
Over 25	30
Types of capital projects	
Buildings	69
Commercial buildings	21
Residential buildings	39
Public buildings	9
Transportation facilities	22
Roadways	15
Bridges	7
Industrial facilities	30
Buildings	21
Utility systems	9
Years of experience as a project manager	
Fewer than 5	30
5–10	51
10–20	33
Over 20	7
Project contract price (in US$ millions)	
Less than 1	33
1–10	57
10–20	15
Over 20	16

3.2. Measures and analysis

Cost, time, and performance are the typical measures of project outcomes (Kloppenborg, Opfer 2002). In other words, a project is often considered healthy (or successful) if it finishes within its budget estimate, finishes within its scheduled time frame, and performs as designed (Scott-Young, Samson 2008). Whilst the research literature in project management engages in a fruitful debate over the nature of project success (Dvir *et al.* 1998), project outcome criteria have become multifaceted.

Thus, this study chooses project time, cost, and profitability as the criteria for capital project outcomes. The rationales are straightforward: delays in completion time may turn a promising investment opportunity into an expensive failure (Scott-Young, Sam-

son 2008), cost overrun directly encroaches on profit (Teerajetgul *et al.* 2009), and project profitability ensures business growth and development (Chen 2011).

In addition, the cost, time, and profitability metrics are objective in nature, allowing a direct comparison of projects with different types, scopes, and sizes across different industries, especially when the metrics are binary measures (Scott-Young, Samson 2008). Consequently, our dependent variable, *Project Outcome*, is binary, with 1 indicating that a capital project finishes within budget and scheduled time frame and makes a profit; otherwise, it is 0.

Measures of project performance variables, including *Scope*, *Quality*, *Team*, *Communication*, *Risk*, *Change*, and *Innovation,* are based on a detailed examination of literature in project management, group effectiveness, organization theory, and innovation management; consultation with several experienced researchers; and consultation with a panel of experts from CNAGC. The work identifies these measures that are similar to the project performance measures most project contracting organizations use internally for assessing the performance of the overall project life cycle. If not otherwise indicated, all measures use a scale in which 1 is "strongly disagree" and 10 is "strongly agree". High scores suggest good performance; low scores indicate poor performance.

Scope ($\alpha = .97$) is measured according to a four-item scale based on Dumont *et al.* (1997), Görög (2011), Ling *et al.* (2009), Kwak and Ibbs (2002), and Roman (1964). The four items are "Quality of contract documents including project definitions, legal terms, specifications, design instructions, and implementation processes is good", "Project owner defines project scope well", "Project owner has verified extent of project scope well", and "Work breakdown structure (WBS) of the project is well defined and manageable".

Quality ($\alpha = .96$) is measured according to a four-item scale based on Ling *et al.* (2009), Roman (1964), and Sperpell (1999). The four items include "Quality-management plan clearly describes how quality assurance (QA) will be performed", "Every quality metric clearly describes what something is and how to measure it", "Quality checklist verifies that a set of required steps is complete", and "Quality baseline is established and well defined".

Team ($\alpha = .98$) is measured according to a 12-item scale based on Anand *et al.* (2010), Bendoly and Swink (2007), Brown *et al.* (1990), Chen *et al.* (2010), Chen and Lee (2007), Hoegl and Parboteeah (2007), Hoegl *et al.* (2003), Hsu *et al.* (2011), Keller (1986), Ling *et al.* (2009), Raiden *et al.* (2004), Scott-Young and Samson (2008), Song *et al.* (2007), Tabassi and Bakar (2009), and Thamhain (2009). Items are "Top management support for the project team is high", "Each team member's project role, responsibilities, and rights are clearly defined", "Enthusiasm about project success is high", "Group participation in decision-making is high", "Interpersonal relationships among team members is good", "Project teams' job skills and expertise are good". , "Degree of cohesiveness of the project team is high", "Degree of motivation of the project team is high", "Degree of cooperation of the project team is high", "Quality of group decisions of the project is high", "Degree of team-building is high", and "Degree of conflict resolution and problem solving of the project team is high ."

Communication (α = .97) is measured according to a six-item scale based on Barclay and Osei-Bryson (2010), Bendoly and Swink (2007), Chen *et al.* (2010), Emhjellen (1997), Huesemann (2006), Ling *et al.* (2009), and Oke and Idiagbon-Oke (2010). The six items are "The project team identifies all the key stakeholders of the project", "The project team meets the information needs of the stakeholders", "The project team meets the communications needs of the stakeholders", "Technology use in information sharing is high", "Communication with the customer is effective", and "Communication within project team members is effective".

Risk (α = .94) is measured according to a four-item scale based on El-Sayegh (2008) and Zou *et al.* (2007). The four items include "Project team handles customer design changes well", "Project team handles lack of defined scope of work well", "Project team handles lack of or departure of qualified staff well", and "Project team handles delays in resolving contractual issues well".

Change (α = .97) is measured according to a three-item scale based on Ibbs *et al.* (2001), Lehmann (2010), and Luu *et al.* (2008). The three items are "The project team continually improves from lessons learned", "The project team brings the appropriate parties into the discussion for the requested change", and "The project team negotiates changes and communicates them to all affected parties".

Innovation (α = .97) is measured according to a 10-item scale based on Ciptono (2006), Dulaimi *et al.* (2005), Kazanjian *et al.* (2000), Keller (1994), Kratzer *et al.* (2006), Miron-Spektor *et al.* (2007), Song *et al.* (2007), and Tranfield *et al.* (2003). Items are "Management support for innovation is high", "Project team applies latest technology to the project", "Project team devotes much time and resources toward generating innovative ideas", "Team members have diverse skills", "Cognitive conflict among project team members is high", "The project manager adopts a bottom-up problem-solving style that incorporates all team members", "There are widespread communications within/across the project", "Extent of elaborating information processing and coordination mechanisms within/across the project is high", "Roles of team members are determined through interaction among project members of different functions", and "The delegation of autonomy and decision authority to the project manager is high".

Confirmatory factor analyses reveal that all the factor loadings of the measurement items of *Scope*, *Quality*, *Team*, *Communication*, *Risk*, *Change*, and *Innovation* are significant ($p < 0.05$) and all are 0.79 or greater, which all exceed the threshold value of 0.5 (Hair *et al.*, 1998). We therefore include all in the project performance measurement model. The resulting measurement model provides a fair fit to the data, with $\chi^2 = 1501$, $df = 860$, RMSEA = 0.08, and CFI = 0.87.

The methodology to analyze the potential predictors of project outcomes is threefold. First, to verify the hypotheses, this study uses the Kolmogorov-Smirnov test to verify normality, followed by T-tests and Mann-Whitney tests, respectively, when the data is normally and abnormally distributed. Subsequent to the equality of mean tests, this study uses univariate logistic-regression analysis to evaluate the variables' predictive ability. Second, based on the significant predictors determined in step one, this study

conducts a hierarchical logistic-regression analysis using a maximum Nagelkerke R-squared improvement procedure to develop optimal project-outcome prediction models. Third, this study evaluates the out-of-sample forecasting accuracy of the prediction models using Type I errors (i.e., a healthy project misclassified as a distressed project), Type II errors (i.e., a distressed project misclassified as a healthy project), and overall correct classification rates.

We split the sample into two subsamples: the estimation data and the out-of-sample forecast data. The estimation data, composed of 80 projects randomly selected from 121 capital projects, are used for the hypothesis tests and model-building. We use the out-of-sample forecast data – the remaining 41 projects – to study the models' predictive ability.

4. Results

4.1. Results of hypothesis tests

Table 2 lists the descriptive statistics and results of Kolmogorov-Smirnov tests, T-tests, and Mann-Whitney tests for the hypothesis. The use of Mann-Whitney tests for *Quality* and *Change* variables is justified by the fact that the data are not normally distributed based on the result of Kolmogorov-Smirnov tests, where the data are judged abnormally distributed when the probability value is smaller than the threshold value of 0.05.

Table 2. Descriptive statistics, Kolmogorov-Smirnov tests, T-tests and Mann-Whitney tests for the hypotheses

Variable	Mean	Minimum	Maximum	Kolmogorov-Smirnov Test N = 80[a]		T-Test N = 80		Mann-Whitney Test N = 80	
				Statistic	Probability	Statistic	Probability	Statistic	Probability
Scope	7.166	3.000	10.000	0.081	0.200	6.496	<0.001	–	–
Quality	7.188	4.000	10.000	0.162	0.000	–	–	332.00	<0.001
Team	7.420	4.000	10.000	0.084	0.200	6.793	<0.001	–	–
Communi-cation	6.959	4.000	10.000	0.094	0.078	5.403	<0.001	–	–
Risk	6.763	3.000	10.000	0.084	0.200	5.984	<0.001	–	–
Change	6.959	3.670	10.000	0.101	0.043	–	–	392.00	<0.001
Innovation	6.724	4.000	9.800	0.099	0.053	4.612	<0.001	–	–

Notes: Project is healthy (= 1), 1 when profitability = 1, cost = 1, and time = 1 exist; otherwise, it is distressed (= 0).
[a]52 projects are healthy, and 28 projects are distressed. Performance ratings of scope, quality, team, communication, risk, change, and innovation were collected right after the end of the initiation and planning phases of a capital project; the contract price and schedule for project change, project actual cost, and project actual schedule were gathered right after the close of the project.

Profitability = Revised profit performance = (revised contract price – actual cost)/actual cost, where the revised contract price includes the cost of scope changes. When larger than 0, it is coded as 1; otherwise, it is 0.

Cost = Revised cost performance = revised estimated cost/actual cost, where the revised estimated cost includes the estimated cost of scope changes. When smaller than 1, it is coded as 0; otherwise, it is 1.

Time = Revised time performance = revised estimated duration/actual duration, where the revised estimated duration includes the estimated duration of scope changes. When smaller than 1, it is coded as 0; otherwise, it is 1.

As the table shows, a significant difference exists in the mean values of distressed and nondistressed projects from *Scope, Quality, Team, Communication, Risk, Change*, and *Innovation* in the project-initiation and planning phases. Significance of difference in means exists when the probability of the Mann-Whitney test and T-test is smaller than 0.05.

All the hypotheses are therefore accepted, suggesting that the *Scope, Quality, Team, Communication, Risk, Change*, and *Innovation* variables in the project-initiation and planning phases possess a potential discriminatory power for differentiating between distressed and nondistressed projects at completion.

This study further performs a series of univariate logistic-regression analyses to evaluate how well these variables differentiate between healthy and distressed projects, as shown in Table 3. The univariate logistic-regression coefficients of *Scope, Quality, Team, Communication, Risk, Change*, and *Innovation* are 1.27, 1.38, 0.88, 0.93, 1.21, 0.68, and 0.89 with *p*-values of <0.01, respectively. The results confirm that *Scope, Quality, Team, Communication, Risk, Change*, and *Innovation* are significant univariate predictors of project outcomes and demonstrate very high classification ability, ranging from 73.75% to 82.50% with Nagelkerke R-squared values from 0.21 to 0.50; *Quality* provides the highest univariate classification accuracy.

Table 3. Univariate logistic analysis results

Variable	B[a]	Exp(B)	Nagelkerke R-squared	Overall Correct (%)
Scope	1.27[**]	3.57	0.49	77.50
Quality	1.38[**]	3.96	0.50	82.50
Team	0.88[**]	2.42	0.29	75.00
Communication	0.93[**]	2.52	0.21	73.75
Risk	1.21[**]	3.36	0.44	78.75
Change	0.68[**]	1.98	0.36	75.00
Innovation	0.89[**]	2.43	0.28	75.00

Notes: [a]Coefficient; [*]$P < 0.05$ and [**]$P < 0.01$.

4.2. Model-building

The hypothesis tests suggest that *Scope*, *Quality*, *Team*, *Communication*, *Risk*, *Change*, and *Innovation* in the initiation and planning phases are significant predictors of project outcomes. Based on the findings, this study further examines whether logit models developed from these predictors differentiate between healthy and distressed projects, making it possible to identify distressed projects early in the process, and thus providing an early warning of distressed projects. This study, therefore, conducts a series of hierarchical logistic-regression analyses using a maximum Nagelkerke R-squared improvement procedure to develop optimal project-outcome prediction models from the estimation data of the 80 projects.

Table 4 reports the model-building results. As the table shows, the optimal project-outcome forecasting model at step 1 (Model 1) is the one with the *Quality* variable, where 50% of the variation in the estimation data is explained; the corresponding Type I error, Type II error, and overall correct classification rates are 32.14%, 9.62%, and 82.50%. At step 2, the optimal project-outcome forecasting model (Model 2), composed of the *Quality* and *Scope* variables, explains 53% of the variation in the performance data, which is 3% more than that of Model 1. The Type I error, Type II error, and overall correct classification rates are 32.14%, 13.46%, and 80.00%, respectively.

The optimal models at steps 3, 4, 5, and 6 (Models 3, 4, 5, and 6) are composed of *Quality*, *Scope*, and *Team*; *Quality*, *Scope*, *Team*, and *Change*; *Quality*, *Scope*, *Team*, *Change*, and *Communication*; and *Quality*, *Scope*, *Team*, *Change*, *Communication*, and *Innovation*, respectively. These models explain 57%, 58%, 58%, and 59% of the variation in the estimation data, respectively. The respective Type I error, Type II error, and overall correct classification rates of Models 3, 4, 5, and 6 are 25.00, 7.69, and 86.25; 25.00, 9.62, and 85.00; 25.00, 9.62, and 85.00; and 21.43, 7.69, and 87.50. Because the Nagelkerke R-square values do not improve after Model 6, Model 7 is not presented in the table. Consequently, Model 6 is the optimal project-outcome forecasting model.

Whilst the correlation matrix reveals that many of the independent variables are more strongly correlated with one another than with the dependent variable *Project Outcome*, detecting multicollinearity that may impair the model's estimated parameters by inflating their variances is important. Table 5 thus reports the multicollinearity diagnostics of Model 6, where the column labeled Condition Number (indicating the square root of the ratio of the largest to smallest eigenvalue) indicates the degree of near-linear dependencies. Eigenvalues have condition numbers larger than 30, and variables with variation proportions greater than 0.5 for each of these eigenvalues are involved in the near-linear dependency (Belsley *et al.* 1980). As the table shows, although the condition numbers of eigenvalues 4, 5, and 6 are larger than 30, only the *Team* variable of the fourth Eigenvalue has a 0.53 variation proportion. This indicates that *Team* is the only variable correlated with the fourth Eigenvalue. Consequently, multicollinearity does not exist in the model.

Table 4. Project-outcome prediction models created with the hierarchical logistic regression using a maximum Nagelkerke R-squared improvement

Variables and Sources	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	B	Exp(B)	B	Exp(B)	B	Exp(B)	B	Exp(B)	B	Exp(B)	B	Exp(B)
Step 1												
Intercept	11.24**	<0.01	−12.05**	<0.01	−12.21**	<0.01	−12.26**	<0.01	−12.80**	<0.01	−13.04**	<0.01
Quality	1.38**	3.96	0.81*	2.25	1.20*	3.32	1.41*	4.11	1.62*	5.05	1.70**	5.48
Step 2												
Scope			0.69	2.00	1.15*	3.15	1.13*	3.10	1.18*	3.25	1.09*	2.98
Step 3												
Team					−0.86	0.42	−0.66	0.52	−0.54	0.58	−0.56	0.57
Step 4												
Change							−0.41	0.66	−0.36	5.70	−0.58	0.56
Step 5												
Communication									−0.37	0.69	−0.45	0.64
Step 6												
Innovation											0.37	1.45
−2 LL	67.87		64.78		61.16		59.89		59.44		59.07	
Nagelkerke R^2	0.50		0.53		0.57		0.58		0.58		0.59	
Type I Error (%)	32.14		32.14		25.00		25.00		25.00		21.43	
Type II Error (%)	9.62		13.46		7.69		9.62		9.62		7.69	
Overall Correct (%)	82.50		80.00		86.25		85.00		85.00		87.50	

Notes: $*P < 0.05$ and $**P < 0.01$.

Table 5. Multicollinearity diagnostics of project-outcome prediction model (Model 6)

Principal Component	Eigenvalue	Condition Number	Proportion of Variation					
			Scope	Team	Quality	Change	Commu-nication	Innovation
1	6.94	1.00	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
2	0.03	15.49	0.02	<0.01	<0.01	<0.01	0.02	<0.01
3	0.01	22.25	0.23	<0.01	0.02	0.20	<0.01	0.07
4	0.01	31.31	0.38	0.53	<0.01	0.06	0.10	0.02
5	0.01	31.93	0.20	0.25	0.24	0.02	0.16	0.08
6	0.00	40.18	<0.01	0.21	0.14	0.32	0.40	0.33

4.3. Evaluation of forecast accuracy

Type I error, Type II error, and overall correct classification rates evaluate out-of-sample forecasting accuracy using data from 41 of the 121 capital projects. Table 6 reports the out-of-sample forecasts from the project-outcome prediction model (Model 6).

Table 6. Out-of-sample forecasts by project-outcome prediction model (Model 6[a])

Project Number	Predictor						$P(Y)$[b]	$\hat{P}(Y)$[c]	Prediction Error[d]
	Scope	Team	Quality	Change	Commu-nication	Innovation			
81	6.75	6.25	9.42	7.33	9.00	7.80	1	0.78	
82	6.50	6.50	6.67	6.50	7.33	6.90	0	0.06	
83	9.50	8.50	8.42	8.17	8.33	8.50	1	0.83	
84	8.00	9.00	9.42	8.83	8.33	7.60	1	0.67	
85	8.00	9.00	9.25	8.33	8.33	7.90	1	0.68	
86	9.00	8.00	8.67	8.00	8.00	8.00	1	0.86	
87	7.00	7.00	8.00	7.17	7.67	6.50	0	0.28	
88	6.75	7.00	7.50	6.67	6.33	5.80	0	0.21	
89	7.25	7.25	8.50	7.83	7.00	7.50	0	0.62	II
90	7.50	8.00	8.58	8.50	9.00	9.00	0	0.40	
91	7.50	7.00	7.83	8.00	8.00	8.00	1	0.33	I
92	6.25	5.25	6.92	6.00	5.00	4.40	1	0.21	I
93	8.75	9.00	9.33	9.00	10.00	9.10	1	0.71	
94	6.00	7.00	6.83	6.50	0.00	2.10	0	0.28	
95	8.75	8.00	8.00	8.00	8.00	7.00	1	0.51	
96	4.75	4.75	5.33	4.33	5.33	5.10	0	0.01	
97	2.50	2.00	3.25	2.50	3.33	3.50	0	0.00	
98	6.75	6.50	7.83	6.50	7.67	7.80	0	0.39	
99	5.50	5.25	6.33	6.83	6.67	5.50	0	0.02	

Project Number	Scope	Team	Quality	Change	Commu-nication	Innovation	$P(Y)$[b]	$\hat{P}(Y)$[c]	Prediction Error[d]
100	5.25	5.00	6.33	4.83	6.33	5.60	0	0.04	
101	6.50	6.50	6.83	7.00	7.00	7.00	1	0.07	I
102	4.75	4.25	5.08	4.50	4.00	3.40	0	0.01	
103	6.75	7.00	7.33	7.00	8.00	7.10	0	0.10	
104	5.25	6.00	5.83	5.50	0.00	1.80	0	0.07	
105	6.00	6.00	5.92	5.83	6.00	5.00	0	0.02	
106	4.25	4.25	4.75	4.00	4.67	4.60	0	0.00	
107	2.00	2.00	2.83	2.00	2.33	2.70	0	0.00	
108	5.75	5.50	6.83	5.50	6.67	6.80	0	0.12	
109	4.50	4.25	5.33	5.83	5.67	4.50	0	0.00	
110	4.75	4.50	5.50	4.50	5.33	5.00	0	0.01	
111	8.50	9.00	9.83	10.00	10.00	9.80	1	0.78	
112	7.50	5.75	7.83	6.50	4.33	4.50	1	0.82	
113	8.75	10.0	9.17	9.00	9.33	9.60	1	0.65	
114	7.50	6.00	8.33	8.00	5.00	6.00	1	0.85	
115	9.50	8.00	8.08	8.17	8.00	7.00	1	0.71	
116	5.25	5.25	5.92	4.67	6.00	5.70	0	0.03	
117	2.50	2.00	3.25	2.50	3.33	3.50	0	0.00	
118	7.75	7.50	8.83	7.50	8.67	8.80	0	0.76	II
119	7.50	7.25	8.00	8.33	8.67	7.50	1	0.22	I
120	5.25	5.00	6.33	4.83	6.33	5.60	0	0.04	
121	7.50	7.00	8.67	6.67	8.33	8.10	1	0.76	

Notes: [a]Model 6 $= -\,13.04 + 1.09Scope - 0.56Team + 1.70Quality - 0.58Change - 0.45\ 0.64Com-munication + 0.37Innovation$, where Nagelkerke $R^2 = 0.59$.

[b]$P(Y) = 1$ when a healthy project exists; otherwise, $P(Y) = 0$.

[c]$\hat{P}(Y)$ is the predicted likelihood of a healthy project by Model 6. The cutoff point is 0.5 (i.e., when it is smaller than 0.5, it is distressed; otherwise, healthy).

[d]I is Type I error, II is Type II error. The average Type I and II errors of out-of-sample forecasts are 23.53% (4/17) and 8.33% (2/24), respectively; the overall correct rate is 85.37% (6/41).

As seen in the table, the respective average Type I error, Type II error, and correct classifications of the out-of-sample forecast data in Model 6 are 23.53%, 8.33%, and 85.37%, respectively; those for the estimation data in Model 6 (see Table 4) are 21.43%, 7.69%, and 87.5%, respectively. The relatively smaller differences in the average Type I error, Type II error, and correct rates for the estimation data and the out-of-sample forecast data in Model 6 indicates that the project-outcome prediction model based on *Scope*, *Team*, *Quality*, *Change*, *Communication*, and *Innovation* is viable and practical.

5. Discussions

The results of this study support the hypotheses that *Scope*, *Quality*, *Team*, *Communication*, *Risk*, *Change*, and *Innovation* in the initiation and planning phases of capital projects possess a potential discriminatory power for differentiating between distressed and nondistressed projects at completion. The findings also indicate that when these variables perform well in the initiation and planning phases of a project, the project is more likely to meet its budget, schedule, and profitability goals. Specifically, our findings reported here suggest that project managers should encourage the development of effective scope management, effective teamwork, risk management, effective communication, innovation, effective quality management, and ability to handle change during a project's initiation and planning phases.

Subsequent univariate logistic analysis results further support the hypotheses that *Scope*, *Quality*, *Team*, *Communication*, *Risk*, *Change*, and *Innovation* in the initiation and planning phases of capital projects are significant predictors of project outcomes assessed on the triple measure set of cost, time, and profitability. The results also show that *Quality* provides the highest univariate classification accuracy; the rest of the variables follow closely, indicating a class of stable predictors. Hierarchical logistic-regression analysis using a maximum Nagelkerke R-squared improvement procedure reveals a high classification accuracy for Models 1 to 6 (see Table 4) that ranges from 80.00% to 87.50% with relatively small difference in the overall classification rates, ranging from 1.25% to 7.50%. The out-of-sample forecasting validation shows that the optimal prediction model (Model 6), composed of *Scope*, *Quality*, *Team*, *Communication*, *Change*, and *Innovation*, provides a reasonably good overall classification rate of 85.37%.

In sum, the findings demonstrate that these variables possess a strong, stable, discriminatory performance for differentiating between healthy and distressed projects. The findings suggest that it is feasible to discriminate simultaneously between healthy and distressed projects prior to the project execution phase in the capital facility delivery process, providing an early warning of projects in distress. It is also significant that these variables hold up as a predictor across different types of capital projects.

Conclusions

Although scope, quality, team, communication, risk, change, and innovation are key determinants of project performance, few studies assess how these variables in the project-initiation and planning phases affect project outcomes. This study therefore investigates the relationship between these variables and project outcomes. The longitudinal data in this study suggest that the variables have a strong, stable, discriminatory power to predict distressed projects. A multivariate logit prediction model on the longitudinal data demonstrates that a combination of *Scope*, *Quality*, *Team*, *Communication*, *Change*, and *Innovation* provides the highest overall classification accuracy for estimation and holdout samples (87.50% and 85.37%, respectively).

Our findings regarding the importance of *Scope*, *Quality*, *Team*, *Communication*, *Change*, and *Innovation* are consistent with prior studies based on the project-execu-

tion phase (e.g., Chen *et al.* 2010; Hoegl, Parboteeah 2007; Keller 1986, 1992, 1994; Tabassi, Bakar 2009; Wang *et al.* 2005) and the overall project life cycle (e.g., Duffy, Thomas 1989; El-Sayegh 2008; Ibbs *et al.* 2001; Ling *et al.* 2009; Oke, Idiagbon-Oke 2010; Scott-Young, Samson 2008; Zou *et al.* 2007). The present research extends the state of knowledge concerning the predictive power of these variables during the successive phases before capital projects become distressed, as well as the relationship between the project-initiation and planning phases and the predictability of distressed capital projects.

As an extension of this research in this paper, a study of the interactions among time, cost and profitability along with the impacts of *Scope*, *Quality*, *Team*, *Communication*, *Risk*, *Change*, and *Innovation* variables would be beneficial because it gives management additional information about not only tradeoffs among time, cost, and profitability, but the critical determinants of each time, cost and profitability in the project-initiation and planning phases.

Another extension of the research to a broader evaluation of these variables that includes NPD and R&D projects will provide management a comprehensive picture of how the predictive power of these variables varies under different types of projects. In another extension of the research to a study of the relationships between improved performance of scope, quality, team, communication, risk, change, and innovation and the likelihood of distress on projects throughout the project-delivery process, it would be beneficial in decision-making, management, and project control.

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