COMPLETING PROJECTS ON TIME AND BUDGET: A STUDY ON THE ANALYSIS OF PROJECT MONITORING PRACTICES USING REAL DATA

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Abstract

This article analyzes the relationship between project cost and time performance indicators and monitoring activities, namely, tracking frequency and regularity with real project data. The existing literature on project monitoring and control remains scant, mainly based on self-reported, simulation-based artificial data for a single project, and somewhat inconclusive. Data from 60 projects managed in Belgium between 2011 and 2019 with different project duration and sizes were first used to reveal associations of regular monitoring with project performance with linear probability models; then, to dissect non-linear associations between monitoring frequency and project performance indicators using random effects models. Earned value management technique with performance indicators is adopted to assess the project performance. Empirical findings indicate that regularly tracked projects are less likely to be late. Tracking frequency displays a U-shaped association with the likelihood of late completion. Moreover, tracking frequency has inverted U-shaped relationships with cost performance and schedule performance indexes. Moving beyond the direct effects, this study is the first to analyze a non-linear relationship between monitoring and project performance. Our results also validate prior studies' findings on regular and frequent tracking effects using real-life multiple-project data and assess the EVM metrics and their behavior in project management.

Keywords

Project management, project monitoring, earned value analysis, project data, regression analysis, panel data

Managerial relevance statement

This research aims to analyze the effects of project monitoring, specifically tracking frequency and regularity, on project time and cost performances using real project data. For project managers, the results highlight the importance and the role of frequency of project monitoring in project performance. A project can suffer in terms of cost and time performance when the project is monitored overly or deficiently. The results of the analysis of real-life multi-project data support the research findings on the regularity and frequency of monitoring of project performance. Considering these results, project managers are encouraged to monitor the projects regularly and make use of the tools that can help them to optimize the monitoring frequency. For this, we suggest developers build tools focusing on the non-linear relationship demonstrated in this study. Additionally, it is essential to develop decision support tools that can assist project managers in defining the monitoring frequency.

1. Introduction

Challenged with various uncertainties of dynamic business environments and severe competitive pressures of industries, project managers monitor several projects simultaneously and are expected to excel in their decisions. Project managers need to detect and diagnose problems swiftly and make decisions to correct them as soon as they occur. Allowing errors can lead to missing project milestones and business objectives and, eventually, project failures. Hence, project managers need to keep track of their projects systematically to improve the effectiveness of their decisions and project performance considerably. In the end, appropriate monitoring and adequate control of the project status is one of the critical success factors for projects [1]. Thus, project managers constantly inquire about possible approaches to monitor project progress closely to avoid potential problems and manage delays and budget overruns [2, 3, 4].

Project monitoring consists of collecting progress data which supports managers in identifying and reporting the status of the project. Control decisions are based on monitoring the schedule and cost realizations/variances of a specific project and analyzing the data collected during project execution. During implementation of the projects, deviations from plans are quite common. To ensure achieving project goals, it is critical to establish effective monitoring and control of the progress, assess the performance by analyzing data, mainly identifying time and cost deviations, and take effective control decisions, which involve the initiation of timely corrective actions such as rescheduling and reallocation of resources [2, 3].

One critical issue in designing control and monitoring approaches is how much monitoring should be exerted and how frequently [5]. Early studies identified parameters and features that a sound control system should possess, varying with the project's size (in terms of duration) and risk level (e.g., Meredith [6]). However, besides these general guidelines, a clear association between project performance and monitoring is needed. This need gave rise to a new stream of research, forecasting aspects of project monitoring, based on predicting the final budget and duration of a project using progress data [7]. For instance, one commonly, extensively used management technique for monitoring the project's performance and forecasting is earned value management (EVM). It is based on comparing the planned and actual project work using monetary units and analyzing the deviations from time-phased budgets.

Like every other approach, EVM is not immune to any criticism. For instance, Henderson [8] questions the reliability of the cost performance index metric of EVM, and others focus on the fact that it does not distinguish between critical and non-critical activities [9]. Vandevoorde and Vanhoucke [10] claim that well-performing activities can neutralize the delay of non-performing activities, arguing that focusing on the project level instead of activities is acceptable. In EVM, behavioral aspects and quality requirements are also disregarded [9].

However, unlike other approaches (such as the critical path method), EVM does not require much effort from project managers to monitor the project, and it has been mandated for many public projects [11, 12]. This can explain its popularity among project managers and why most software packages embed EVM metrics.

Project managers can benefit prominently from developing a structured progress monitoring, performance assessment, and managerial control system [13]. However, empirical studies on project management decision-making, specifically on monitoring and control, remain scant compared to other areas of business studies and are somewhat inconclusive. Most existing studies analyze the causes of cost and time overruns or develop monitoring and control techniques [14]. Prior studies focused on monitoring and control techniques to design a monitoring system, which involves decisions on the timing and frequency of control points and intensity of control activities (e.g., Partovi & Burton [15]; Snider et al. [16]). However, these studies analyze the effect of monitoring mainly using surveys (e.g., Mahaney & Lederer [17]), interviews (e.g., Mahaney & Lederer [18]), modeling (e.g., Raz & Erel [5]) and simulation experiments (e.g., Partovi & Burton [15]). Most of these studies were also based on single-project organizations, unlike usual multi-project environments [19]. Nevertheless, some studies found monitoring effective only under specific conditions (e.g., Parks & Conlon [20]) or had inconclusive results (e.g., Dalton et al. [21]).

Methodological limitations of prior studies and the inconclusive results suggest the need for research on the effect of tracking frequency and regularity of monitoring and control on project performance with real-life multiple project data. Researchers require real project data to test and improve performance of algorithms and decision support tools. However, availability of such data is a critical concern for researchers [22] as publicly available databases are very rare. Considering this essential need, Batselier and Vanhoucke [23] and Thiele et al. [24] share their real-life project databases that we use in this study. We conduct empirical analyses to provide insights on project monitoring and performance assessment. More specifically, we investigate the impact of tracking frequency and regularity on project time and cost performance. To the best of our knowledge, there is no study that examines these relationships using multiple real project data. By analyzing the effects of monitoring on performance, this paper attempts to make three main contributions. First, our study verifies prior studies' findings by explicitly analyzing the effects of regular and frequent tracking by using real-life multiple-project data. Second, by moving beyond the direct effects, this study is the first to empirically analyze a non-linear relationship between tracking frequency and project performance (for both cost and time performance). Third, we assess the EVM metrics, CPI and SPI, and their behavior in project management. Our findings also provide insights to project managers on how to enhance their project monitoring and control.

The article is organized as follows; in the following section, we introduce our hypotheses, then we present the data and our research methodology. Later, we present our empirical results. Finally, we discuss theoretical and managerial implications, along with limitations and some promising research avenues.

2. Hypothesis development

Project performance is usually judged based on the cost, completion time, and the extent to which requirements are met. Project costs and schedules are often underestimated in the initial planning phase; hence projects require an iterative scheduling and cost development process [25]. Deviations from the baseline schedule and the scope during project execution often lead to delays and increased costs at completion [26]. Monitoring the progress involves measuring the performance of an ongoing project and detecting deviations from the plan throughout the project life cycle by regularly tracking the time and cost data. Analysis of this data allows us to take necessary corrective actions to achieve the project objectives and positively contribute to the overall progress of the project [27]. The survey results of White and Fortune [28] also presented that effective monitoring and feedback are some of the critical factors in completing the project on time and within budget.

Specifically, anticipating delays in project activities and making efforts accordingly can positively impact the final project duration. Delays in some activities might not only affect subsequent activities but also create resource conflicts and lead to overall project overruns [29]. Most late projects experience cost overruns as well [30, 31]. The longer the project delays, the higher the cost overruns will be. Effective monitoring and control practices can reduce such overruns [31]. As prior studies emphasized, managers are more effective when they perceive what needs to be done; hence tracking can be used to achieve successful project completion. Project managers can avoid project delays and overruns if they conduct project tracking at periodic intervals [32].

One way to track project performance is using EVM, which allows for analyzing the progress data. Specifically, the cost performance index (CPI) and schedule performance index (SPI) reflect the actual progress as a ratio of the planned progress and cost spending. CPI is calculated by dividing earned value (EV) to the actual cost (AC), and SPI by dividing the EV to the planned value (PV). Thus, based on CPI and SPI, a project manager can evaluate the project progress at a certain point and can decide to take some corrective actions.

Even though CPI and SPI are well-known performance indicators, their behavior is not entirely well apprehended [12]. CPI is used as a reliable cost-efficiency indicator that presents the cumulative cost efficiency of a project [33]. A CPI value below 1 indicates that the project cost is over budget. CPI can also be used to track periodic results, for parts of a project or shorter periods [34]. While the research on EVM has been mainly cost-driven, lately, there has been a growing interest in the time dimension of EVM as well [35]. SPI is a measure to assess the project’s progress. When it is less than one, the project is behind schedule. Recent studies presented new EVM methods (e.g., planned value method, PVM, and the earned duration method, EDM) that still rely on SPI to measure a project’s time progress and predict the final duration of a project [36]. While there are criticisms of the reliability of SPI [12], it is still an acceptable performance indicator.

Both CPI and SPI can also be used to predict the ultimate project performance [34]. The milestone-level analysis of CPIs and SPIs is particularly useful in addressing the budget and time of individual deliverables in a project [37]. As Fleming and Koppelman [34] stated that a successful EVM implementation requires that only authorized and budgeted tasks are accomplished, and the effort being made must be tightly controlled. Since projects might have unexpected deviations from the baseline schedule and cost estimates, measuring the performance is crucial. Thus, it is expected that project tracking would have a positive effect on CPI and SPI. Thus, we propose that:

Hypothesis 1: Monitoring and control of the project progress at regular intervals has a negative association with the probability that a) project finishes late and b) has a positive association with project schedule performance index (SPI).

Hypothesis 2: Monitoring and control of the project progress at regular intervals a) has a negative association with the probability of project cost overrun and b) has a positive association with project cost performance index (CPI).

The frequency of monitoring is as important as the content of monitoring itself for the success of a project. It provides more accurate data about the project status and assists in spotting complications at an earlier stage. Thus, frequent monitoring helps project managers to reduce costs and time overruns. While prior studies emphasized the importance of monitoring, projects often have inconsistent monitoring and control [38], so projects often lack periodic checks [32].

For instance, some projects are still monitored less than quarterly [39]. Couillard [40] presented that a higher frequency of project monitoring and control improves the likelihood of project success, specifically when technical, cost, and schedule risks are high. Enshassi [41] also highlighted the importance of frequent monitoring, as monitoring projects frequently allows a manager to control a project better by constraining, coordinating, and regulating actions accordingly [42]. Lewis et al. [43] also disclosed that frequent monitoring was required to reduce uncertainty during the early stages of a project and during the later stages to promote project completion. Thus, frequent tracking is essential for achieving project goals.

Establishing an effective monitoring system has been previously studied in the literature (e.g., Raz & Erel, [5]). There are some studies conducted to determine the optimal timing of project control points in the project's life cycle. De Falco and Macchiaroli [33] proposed a model to assist project managers' decisions regarding the timing and frequency of control based on the definition of an effort function. Their study presented a non-linear function, an inverted U-shape, between control intensity efforts. A review in the field of strategy research also presents increasingly explored non-linear relationships that often follow an inverted curvilinear-shaped pattern that first increases at a decreasing rate to reach a maximum point and then decreases at an increasing rate [44]. Such a relationship presents that optimal performance can be reached with moderate levels of strategy. Following the study of De Falco and Macchiaroli [33], we theorize a curvilinear relationship between monitoring and project success since staying on schedule and budget is considered as a successful project.

In the project management context, prior studies examining the role of senior management involvement with project quality presented that too much involvement of such key decision-makers may lead to detrimental effects, presenting an inverted U-shaped relationship (e.g., Bonner et al. [45], Unger et al. [46]). Excessive mentoring by senior management would lead to over-commitment, micro-management, or allocation of an unjustifiable amount of resources

[46, 47]. Studies focusing on supervision and performance also demonstrated that the supervisor's moderate levels of close monitoring could enhance individual or partner creativity. However, very low or very high levels of supervision can diminish their creative performance [47]. Excessive monitoring may undermine the project performance at some point, leading to distrust between parties and over-commitment of the project manager. Such extreme tracking can waste resources in terms of time and money. With CPI and SPI project performance measures, an inverted-U-shaped relationship could be expected where moderate monitoring levels are associated with higher project performance while low and high monitoring levels are associated with low project performance. Thus, we argue for an inverted curvilinear relationship between monitoring and project performance which can be measured by CPI and SPI. Hence, we propose the following:

Hypothesis 3: Frequency of project monitoring is nonlinearly associated with a) the probability that project finishes late and b) with the schedule performance index (SPI).

Hypothesis 4: Frequency of project monitoring is nonlinearly associated with the probability that a) project cost overrun and b) with cost performance index (CPI).

3. Data and Methodology

3.1. Project Data

This study investigates the associations of project monitoring activities with project performance indicators. To achieve this, this study uses data from real projects from construction sector introduced by Batselier and Vanhoucke [23] and Vanhoucke et al. [35]. The original data set composed of 133 projects conducted in Belgium from various sectors is extracted from a website with detailed project information, risk measures, and progress indicators [48]. Certain conditions are introduced for projects to be employed in empirical analysis: (1) the project must have tracking information; (2) the project must belong to the construction sector (3) the project must not be an outlier for the number of tracking periods. Namely, projects with a total number of tracking periods ranging from 4 to 16 are considered for data analysis. One hundred ten projects, out of 133, provide tracking information. Seventy-eight projects out of 110 are listed for the construction sector. Sixty projects out of 78 have at least four and at most 16 tracking periods. Hence, 60 projects that were managed between 2011 and 2019 with different project duration are included in this study (See Table 1 for the final sample). This study analyzes the data collected from real projects and utilizes EVM metrics to assess performance. Our analysis focuses on the relationships between progress monitoring and performance assessment.

3.2. Construction of Data Sets and Variables

In order to test our hypotheses on relations among monitoring activities and project performance indicators, we built two data sets, a cross-section and a balanced panel, using data from 60 real construction projects (See Figure 1). Both data sets include project characteristics such as planned/actual cost, planned/actual duration, planned/earned value, tracking regularity, number of tracking periods, percentage completion, schedule variance, and cost variance. Descriptions of all variables used for our data analysis are provided in Table 2.

First, we built a cross-sectional data set to study performance indicators at project completion. Due to the lack of available data and small sample sizes in real project data, researchers had to use limited variables to study project management [49, 50]. Similar to earlier studies (e.g., Adoko et al [49]), we employ binary dependent variables, such as *Late Completion* and *Over Budget*, for project performance indicators. *Late Completion*, measuring the time performance of a project, is equal to one if the actual duration of the project is greater than the planned duration and equal to zero otherwise. *Over Budget*, an indicator of the budget performance, is equal to one if the actual cost of the project is greater than the planned value and equal to zero otherwise. We set up two variables for tracking characteristics of the project: (i) *Regular Tracking* and (ii) *Tracking Frequency*. *Regular Tracking* is a dummy variable to display whether the project is regularly tracked or not. *Tracking Frequency* is defined as the total number of tracking periods per hundred actual duration days at the end of a project. We also used actual cost and actual project duration as control variables.

To analyze cost and schedule performance indicators over time, we built a balanced panel. We redefined the time dimension as quarterly to measure tracking frequency; hence four tracking quarters are defined for each project. Due to the nature of the data, monitoring frequency indicators are cumulatively measured in our panel data set. *Cumulative Number of Tracking Periods* is equal to the total number of tracking controls for the end of the corresponding quarter control period. *Cumulative Tracking Frequency* is defined as the cumulative number of tracking periods per hundred cumulative actual duration days for each quarter. We use earned value, planned value and actual cost data from quarter control periods of each project to construct *Schedule Performance Index (SPI)* and *Cost Performance Index (CPI)* for corresponding quarters. Table 2 presents measurement details and formulations of each variable for both datasets.

3.3. Method

We employed various regression models for our data analysis and hypothesis testing. Figure 1 displays the flow chart of our data collection and methodological framework. First, we utilized our cross-sectional data set to estimate probability models for late completion and over-budget statuses of projects (See Section 3.3.1). Next, we employed regression models with our balanced panel data for project performance indicators, *SPI* and *CPI*, to estimate random effects models, which are described in Section 3.3.2.

3.3.1. Linear Probability Model

For cross-sectional analysis, probability models are utilized to investigate associations of late completion and over-budget statuses of projects with tracking properties. Since *Late Completion* and *Over Budget* are binary variables, binary response empirical models would be an appropriate methodology. Among binary response models, we employed a linear probability model since these models are easier to estimate and interpret. Although linear probability models require relatively fewer assumptions on data structure, they can also predict out-of-range probabilities for extreme values in the data set [50]. Thus, we also use a non-linear probability estimation framework, probit regression, for robustness check. Theoretical regression line for our linear model is presented below:

$$Pr(Y_i=1|X=x) = \alpha_0 + \alpha_1 Regular\ Tracking_i + \alpha_2 Tracking\ Frequency_i + \alpha_3 Tracking\ Frequency_i^2 + \sum_{j=1}^{3} \beta_j Actual\ Cost\ Category_{ji} + \sum_{k=1}^{3} \delta_k Actual\ Duration\ Category_{ki} + e_i$$

where Y_i refers to our dependent variables for each project i (Late Completion and Over Budget); X represents vector of explanatory variables and e_i is the error term of the model.

Linear probability models are estimated with ordinary least squares methodology using STATA 15 software [51]. Since all probability models are heteroscedastic [52], robust standard errors are used in estimations.

3.3.2. Random Effects Model

Since we have a real project data set with limited information, we employed random effects regression models for our panel data analysis to investigate associations of performance indicators (SPI and CPI) with tracking activities. Random effects models account for unobservable project-specific characteristics and interdependency of panel observations. In order to quantify associations of project characteristics with continuously measured EVM indicators, we utilize random effects models of panel data. Although *SPI*, *CPI*, and *Cumulative*

Tracking Frequency vary over time, project characteristics such as *Regular Tracking*, *Actual Cost Category*, and *Actual Duration Category* are time-invariant. This prevents us from using standard regressions or fixed effects framework, but not the random-effects modeling since most of our explanatory variables are constant over time [52]. Since *SPI* and *CPI* are cumulative, we also included the first lag of these variables in our estimations to restrict endogeneity problems. In order to test our hypotheses on the impacts of regular tracking and tracking frequency on SPI and CPI, we include regular tracking and cumulative tracking frequency variables in the regression equation. Hypotheses on the non-linearity of associations between tracking frequency and performance indicators are tested by including the square of cumulative tracking frequency measure in our models. Hence, regression equation for our random effects model is given below:

$$Performance\ Index_{it}=\theta_0+\theta_1 Performance\ Index_{it-1}+\theta_2 Regular\ Tracking_i$$

$$+\theta_3 Cumulative\ Tracking\ Frequency_{it}+\theta_4 Cumulative\ Tracking\ Frequency_{it}^2$$

$$+\sum_{j=1}^{3}\mu_j TotalActual\ Cost\ Category_{ji}+\sum_{k=1}^{3}\rho_k Total\ Actual\ Duration\ Category_{ki}+\alpha_i+u_{it}$$

where Performance $Index_{it}$ refers to our dependent variables (*SPI* and *CPI*) for each project i at quarter t; α_i is the unobserved/random effect, u_{it} is the error term of the model. Generalized least squares methodology is applied using STATA 15 software [51] with robust standard errors that are clustered at the project level in model estimations. All models include lag of the dependent variable to address endogeneity issues, cost levels, and duration levels as control variables.

4. Empirical Results

A total of 60 projects from the construction sector are considered for empirical analysis. 65% of projects were completed late, and 73.3% had a budget overrun. 66.7% of projects were regularly tracked and the average for the total number of tracking periods per project was 7.4. The average tracking frequency for projects corresponds to approximately 4 per hundred actual duration days, with a minimum of 1.5 and a maximum of 7.69. The average actual duration of projects is 207.6 working days. 25% of projects were relatively short, with actual duration ranging from 75 to 100 days. On the other hand, 16.67% of projects had a total actual duration between 300 and 600 days. 35% of all projects had relatively lower actual cost figures than 250,000 Euros, whereas 21.67% were conducted with an actual cost higher than 1.5 million Euros. SPI ranges from 0.175 to 74.925 and displays an average of 1.252. CPI has an average of 0.955 and varies between 0.477 and 1.568. Descriptive statistics for each data set are presented in Table 3.

4.1. Cross-Sectional Findings

We use cross-sectional data to estimate linear probability models for late completion and over-budget statuses of projects with tracking activities. First, we estimate simple regression models for each independent variable to see the contribution of each variable to the model; then, we construct a complete model with all variables of interest. Once we introduce control variables, Model 6 reveals that regular tracking and late completion are negatively correlated ($p<0.05$, See Table 4). R-squared around 0.39 confirms the adequacy of the model. Thus, the results of Model 6 show that regular tracking is associated with a decline of 25.6 percentage points in the probability of late completion. This finding is also robust to model choice based on the probit model estimation results (See Appendix Table). Overall, findings from Models 1 and 6 indicate that regular tracking is negatively associated with the probability of late completion and support Hypothesis 1a.

Even though Model 2 (in Table 4) is not overall significant with a low R-squared value, Model 3 implies a U-shaped relation between the probability of late completion and tracking frequency. For lower levels of tracking frequency, a negative relationship between tracking frequency and the probability of late completion is found. Whereas, for higher values of tracking frequency, there is a positive relationship between tracking frequency and the probability of late completion. Namely, scant and excessive tracking approaches are associated with a higher probability of late completion. This finding is confirmed by Model 6 of Table 4 at higher levels of significance, i.e., 5% for tracking the frequency and 10% for the square of tracking frequency. Probit regression estimations, presented in Appendix, reveal similar results. Overall, empirical findings support Hypothesis 3a by revealing a non-linear association between tracking frequency and the probability of late completion. Additionally, Models 4 and 6 of Table 4 imply that relatively low-cost projects are less likely to be completed late.

Empirical results for linear probability models of going over budget are reported in Table 5. Models 1 and 6 reveal no significant association between regular tracking and project budget overrun statuses. Hence, empirical findings do not support Hypothesis 2a. Similar findings from a probit framework are presented in the Appendix. Likewise, Models 2 and 3 present no significant relationship between budget overrun and tracking frequency. Overall, empirical findings do not support Hypothesis 4a and imply no curvilinear associations between tracking frequency and the probability of project cost overrun. Moreover, Models 4 and 6 suggest no correlations between the level of actual cost and the probability of running over budget. Finally, Models 5 and 6 indicate that projects with relatively lower duration are more likely to have a cost overrun.

4.2. Panel Findings

Estimation results from random effects models of SPI (Model 1 to 3) and CPI (Model 4 to 6) are presented in Table 6. Models 1 and 3 (including all control variables) do not support Hypothesis 1b because the coefficient estimate for regular tracking is insignificant. These findings suggest regular tracking is not correlated with SPI based on panel data. However, Models 2 and 3 estimate significantly positive coefficients for cumulative tracking frequency *(M2, β = 0.160, $p \leq 0.01$; M3, β = 168, $p \leq 0.01$)* and negative coefficients for the square of cumulative tracking frequency *(M2, β = -0.0143, $p \leq 0.01$; M3, β = -0.0151, $p \leq 0.01$)*. These results indicate a non-linear relationship between SPI and cumulative tracking frequency. While there is a negative association between cumulative frequency and SPI across lower levels of cumulative frequency, a positive correlation is also found between these variables at higher levels of cumulative tracking frequency. In sum, the findings of Models 2 and 3 imply that there is an inverted U-shaped association between cumulative tracking frequency and SPI. Hence, empirical results from panel data support Hypothesis 3b.

By testing for associations of SPI with project characteristics, we also found no support for the relation between total cost levels and SPI of projects. Model 1 also implies that projects with a longer duration have lower SPI *($p \leq 0.1$)*. Confirming the relationship between past and current performances, Models 1, 2, and 3 indicate that lag of SPI is positively associated with current SPI. Hence, projects that perform better in achieving their targets for scheduling in the previous quarter are more likely to have better SPI in the current quarter.

Models 4, 5, and 6 in Table 6 display the estimation results of CPI. Model 6, which includes all control variables, reveals that, ceteris paribus, regular tracking is not significantly associated with CPI. This is also supported by Model 4, which reports an insignificant coefficient for regular tracking. Hence, empirical results from random effects models do not support Hypothesis 2b, indicating nonsignificant correlations between regular tracking and cost performance. However, Models 5 and 6 support Hypothesis 4b since they yield positive and significant coefficient estimates for cumulative tracking frequency *(M5, β = 0.0371, $p \leq 0.05$; M6, β = 0.0541, $p \leq 0.0$)* and negative coefficients for the square of cumulative tracking frequency *(M5, $\beta = -0.00494$, $p \leq 0.01$; M6, $\beta = -0.00662$, $p \leq 0.01$)*. For lower levels of cumulative frequency, there is a negative association between cumulative frequency and CPI, whereas this correlation appears to be positive for higher levels of cumulative tracking frequency. Hence, we observe a non-linear, inverted U-shaped relationship between CPI and cumulative tracking frequency.

The relationship of project characteristics with CPI is also examined and presented that the total cost level for projects is not significantly associated with CPI over quarters based on the estimation results of Models 4, 5, and 6. Although Models 5 and 6 display no statistically meaningful relationships between project duration and CPI, Model 4 displays that projects with the highest duration (300 to 600 days) have lower CPI at a 10% significance level. Findings of random effect models also imply that the lag of CPI has a positive relationship with the current CPI at 1% level. In other words, real project data confirms that the previous cost performance of projects is positively associated with current cost performance.

Overall, we report a summary of our hypothesis testing results in Table 7. Cross-sectional findings reveal that regularity and frequency of tracking are associated with the project's completion time. On the other hand, the budget overrun status of the project is not correlated with regular tracking and monitoring frequency. Panel data findings provide empirical evidence for non-linear associations of monitoring frequency with SPI and CPI. However, there is no evidence for associations of SPI and CPI with the regularity of tracking.

5. Discussion

This study empirically investigates associations between the monitoring, including monitoring frequency and regularity, and project performance. Based on the 60 real-life projects from the construction sector, we measure the project performance in terms of cost and time and present clear implications for theory and practice.

Prior studies stated that regular project monitoring could be used to achieve successful project completion by using it as a control to reduce project delays [e.g., 28, 30, 32]. Our real-life multiple-project data analysis results confirm that late completion is diminished by regular tracking; however, we could not find any support for a positive effect to decrease the cost overruns. This could also be related to the nature of construction projects. The construction industry does not have good statistics on finishing projects within budget, even though the initially assigned budgets have increased compared to previous years [53]. Thus, even regular monitoring may not be sufficient to control cost overruns.

Our results also demonstrated that EVM metrics could be useful indicators that are nonlinearly associated with project tracking frequency. The result could be due to the nature of the controls, namely the effects of scheduled project progress controls versus unscheduled frequent progress checks. Project workers who are aware of the schedule typically adjust their work priorly [54] and distribute their efforts regularly [55]. However, frequent unscheduled monitoring requires sudden, increased efforts from project workers, demanding them to switch their efforts to the specific project [54]. This can also explain the nonlinear relationship between monitoring frequency and project performance as the positive effect of monitoring decreases with cumulative monitoring events for workers to build insensitivity to monitoring events and reluctance to switch and increase the costs yielded by excessive measures [54, 56]. Furthermore, in less frequent controls, the project manager limits the variables in their analysis and reports, possibly missing some relevant ones, but this might not be the case in frequent ones. These findings are especially noteworthy with the rise of organizational structures oftentimes engaging managers in multi-project settings and increased uncertainty in the environment for monitoring activities [57].

5.1. Theoretical Contributions and Managerial Implications

By examining the relationships between monitoring and project performance, our results contribute to the literature in several ways. First, our study extends previous research on the relationship between monitoring and project performance by testing and supporting the role of regular and frequent project monitoring with actual project data. In an effective project management practice, it is critical to determine the optimal amount and timing of project monitoring. However, this area is rather unlooked by the prior studies that mainly analyzed the advanced monitoring techniques or the causes of cost and time overruns [14]. As previously stated, there is also a lack of empirical analysis supporting this relation due to the methodological limitations of self-reported and simulation-based artificial data, often based on single projects (e.g., Partovi & Burton, [15], Mahaney & Lederer, [17, 18]).

Secondly, incorporating the widely used EVM method of project managers, this study expands the literature with a limited analysis of EVM performance metrics [58]. Using the EVM method with CPI and SPI indicators is a common way to measure the overall project performance. Hence, our results also allow a better comprehension of the behavior of EVM metrics, which was somewhat lacking [12] and has been subject to criticism (e.g., Henderson [8]). As our results present, CPI did not prove to have strong predictive quality. This could support the existing criticisms for using CPI (e.g., Lipke et al [12]). However, the results present that EVM metrics could be useful indicators that are nonlinearly associated with project tracking frequency.

Third, the present study is also one of the first to suggest a nonlinear relation between the monitoring frequency and performance with an empirical analysis with real data that a project suffers in terms of cost and time performance when the project is monitored overly or deficiently. This area was somewhat neglected within project management; only a few analyzed the relationship between performance and project quality [e.g., Bonneret et al [45], Unger et al [46]] and monitoring with individual-level creativity (e.g., Lee et al [47]). Even though

Couillard [40] and Lewis et al. [43] presented the importance of frequent monitoring to reduce uncertainty and promote project completion, our results present a nonlinear relation between the monitoring frequency and performance, confirming the proposed model of De Falco and Macchiaroli [33] with actual project data. Our findings present that moderate levels of monitoring are associated with higher project performance, while low and high levels of monitoring are associated with low project performance. While moderate levels of monitoring reduce uncertainty and promote project success, high levels of monitoring by project managers might be perceived as micro-management. Intensive monitoring might also require the allocation of excessive resources and lead to distrust between involved parties in the project, which can cause other detrimental effects.

Our study contributes to project management practice by demonstrating the importance and the role of regular and frequent project monitoring in project performance. Therefore, project managers are encouraged to work on optimizing the monitoring frequency during the project's lifetime. Doing so would give them the information to act on to avoid cost overruns and project delays. To achieve this, diverse methods such as simulation and optimal control and decision support systems can inform managers about the optimal frequency [59]. Thus, it is essential to develop tools that can assist project managers in defining the optimal monitoring frequency so that managers can focus more on taking corrective actions. Our results also indicate that not all EVM metrics are reliable indicators; hence project managers should handle them with caution when controlling their projects based on CPI.

5.2. Limitations and Future Research Directions

This study has multiple methodological limitations. First, due to the scarcity of public data on project management, this study utilizes actual project data that is secondary and collected from a single country. Future research with more extensive data sets would be necessary to test the robustness of our findings. Moreover, we focused on construction sector projects due to heterogeneity issues across sectors. Even though different projects may require different monitoring frequencies, within a single industry, such as construction projects, variations were not observed. The findings of our study can construct an empirical base for future studies. Second, we lack information regarding the type of monitoring (i.e., reports, statistics, informal/formal monitoring, or participatory reviews), the type of reporting and tools (if used), and the level of details used during the project tracking, and how this variation impacts the project completion. Future studies should also investigate these differences to optimize the monitoring process. Third, although we introduce control variables, we cannot eliminate the potential of omitted variables due to data availability issues. Future studies may incorporate additional variables for project characteristics, such as industry type and complexity measures. Fourth, the analysis of this study is based on correlational designs, so the current study's findings are prone to simultaneous causality issues and should be cautiously interpreted. Future research may focus on establishing causality dimensions for tracking and performance measures of projects. Fifth, our balanced panel was constructed based on quarters to improve our understanding of non-linear associations. However, there is heterogeneity in the length of quarters across projects due to their total duration. Further studies may consider samples of projects with the same quarter length and/or panel data based on higher frequencies, such as monthly data. The current study does not aim to analyze the optimal monitoring frequency and length of a control cycle. Future studies may provide insights into optimal monitoring dynamics with appropriate data and methodology. Finally, as previously mentioned, EVM is subject to certain limitations due to its assumptions. As a technique, EVM does not address quality, uncertainty, risk, opportunity, and skill status (e.g., Browning [60]; Liu & Yokoyama [61]); future studies could incorporate these attributes.

5.3. Conclusion

Even though prior studies have acknowledged the importance of monitoring to achieve better project performance, there was a lack of empirical analysis to illustrate this with real multiple project data. Thus, this study analyzes the associations between project monitoring practices with project time and cost performance based on real project data. The results underline that regular monitoring and frequency of monitoring have significant roles in project management. Additionally, results present that a project suffers in terms of cost and time performance when the project is monitored overly or deficiently. Thus, this study expands the field with a specific focus on project monitoring and assists in understanding why certain projects fail, yet others succeed.

References

[1] Royer, P. S. (2000). How healthy is your project? Paper presented at Project Management Institute Annual Seminars & Symposium, Houston, TX. Newtown Square, PA: Project Management Institute.

[2] Shtub A, Bard J, Globerson S (2014) *Project Management: Processes, Methodologies, and Economics.* (New International Edition) Prentice Hall, NY.

[3] Pellerin, R., Perrier, N. (2019). A review of methods, techniques and tools for project planning and control. *International Journal of Production Research, 57*(7), 2160-2178.

[4] Mahmoudi, A., Bagherpour, M., & Javed, S. A. (2019). Grey earned value management: theory and applications. *IEEE Transactions on Engineering Management* 1-19.

[5] Raz, T., Erel, E. (2000). Optimal timing of project control points. *European Journal of Operational Research, 127*(2), 252-261.

[6] Meredith, J. R., Shafer, S. M., & Mantel Jr, S. J. (2017). *Project management: a strategic managerial approach*. John Wiley & Sons.

[7] Colin, J., Martens, A., Vanhoucke, M., & Wauters, M. (2015). A multivariate approach for top-down project control using earned value management. *Decision Support Systems*, 79, 65-76.

[8] Henderson, K. (2008). Does project performance stability exist? a re-examination of cpi and examination of spi (t) stability. Cross Talk.

[9] Hall, N. G. (2012). Project management: Recent developments and research opportunities. *Journal of Systems Science and Systems Engineering*, 21(2), 129-143.

[10] Vandevoorde, S., & Vanhoucke, M. (2006). A comparison of different project duration forecasting methods using earned value metrics. *International Journal of Project Management*, *24*(4), 289-302.

[11] Kim, E. H., Wells, W. G., Jr., & Duffey, M. R. (2003). A model for effective implementation of earned value management methodology. *International Journal of Project Management*, 21(5), 375–382.

[12] Lipke, W., Zwikael, O., Henderson, K., & Anbari, F. (2009). Prediction of project outcome: The application of statistical methods to earned value management and earned schedule performance indexes. *International Journal of Project Management*, *27*(4), 400-407.

[13] Rozenes, S., Vitner, G., & Spraggett, S. (2006). Project control: literature review. *Project Management Journal*, *37*(4), 5-14.

[14] Olawale, Y., & Sun, M. (2015). Construction project control in the UK: Current practice, existing problems and recommendations for future improvement. *International journal of project management*, *33*(3), 623-637.

[15] Partovi, F. Y., Burton, J. (1993). Timing of monitoring and control of CPM projects. *IEEE Transactions on Engineering Management, 40*(1), 68-75.

[16] Snider, C., Gopsill, J. A., Jones, S. L., Emanuel, L., & Hicks, B. J. (2019). Engineering project health management: a computational approach for project management support through analytics of digital engineering activity. *IEEE Transactions on Engineering Management, 66*(3), 325-336.

[17] Mahaney, R. C., & Lederer, A. L. (2006). The effect of intrinsic and extrinsic rewards for developers on information systems project success. *Project Management Journal, 37*(4), 42-54.

[18] Mahaney, R. C., & Lederer, A. L. (2003). Information systems project management: an agency theory interpretation. *Journal of Systems and Software, 68*(1), 1-9.

[19] Hazır, Ö. (2015). A review of analytical models, approaches and decision support tools in project monitoring and control. *International Journal of Project Management, 33*(4), 808-815.

[20] Parks, J. M., & Conlon, E. J. (1995). Compensation contracts: do agency theory assumptions predict negotiated agreements? *Academy of Management Journal, 38*(3), 821-838.

[21] Dalton, D. R., Daily, C. M., Ellstrand, A. E., & Johnson, J. L. (1998). Meta-analytic reviews of board composition, leadership structure, and financial performance. *Strategic Management Journal, 19*(3), 269-290.

[22] Hall, N. G. (2016). Research and teaching opportunities in project management. In *Optimization Challenges in Complex, Networked and Risky Systems*, pp.329-388, INFORMS.

[23] Batselier, J., Vanhoucke, M. (2015). Construction and evaluation framework for a real-life project database. *International Journal of Project Management*, *33*(3), 697-710.

[24] Thiele, B., Ryan, M., & Abbasi, A. (2020). Developing a Dataset of Real Projects for Portfolio, Program and Project Control Management Research. *Data in Brief, 34*, 106659.

[25] Taylor, J. (2008). *Project scheduling and cost control: planning, monitoring and controlling the baseline*. J. Ross Publishing.

[26] Nelson, R. R. (2007). IT project management: Infamous failures, classic mistakes, and best practices. *MIS Quarterly Executive*, *6*(2), 67-78.

[27] Pajares, J., & Lopez-Paredes, A. (2011). An extension of the EVM analysis for project monitoring: The Cost Control Index and the Schedule Control Index. *International Journal of Project Management*, *29*(5), 615-621.

[28] White, D., & Fortune, J. (2002). Current practice in project management—An empirical study. *International Journal of Project Management, 20*(1), 1-11.

[29] Song, J., Martens, A., & Vanhoucke, M. (2020). The impact of a limited budget on the corrective action taking process. *European Journal of Operational Research, 286*(3), 1070-1086.

[30] Frimpong, Y., Oluwoye, J., & Crawford, L. (2003). Causes of delay and cost overruns in construction of groundwater projects in a developing countries; Ghana as a case study. *International Journal of Project Management*, *21*(5), 321-326.

[31] Morris, P. W., & Hough, G. H. (1987). *The anatomy of major projects: A study of the reality of project management*. John Wiley, New York.

[32] Kursave, J. D. (2003). The necessity of project schedule updating/monitoring/statusing. *Cost Engineering*, *45*(7), 8-14.

[33] de Falco, M., & Macchiaroli, R. (1998). Timing of control activities in project planning. *International Journal of Project Management, 16*(1), 51-58.

[34] Fleming, Q., & Koppelman, J. M. (2009). The two most useful earned value metrics: the CPI and the TCPI. *Cost Engineering*, *51*(3), 16-18.

[35] Vanhoucke, M., Coelho, J., & Batselier, J. (2016). An overview of project data for integrated project management and control. *Journal of Modern Project Management, 3*(3), 6-21.

[36] Jacob, D. (2003). Forecasting project schedule completion with earned value metrics. *The Measurable News*, *1*(11), 7-9.

[37] Willoughby, T. J. (1995). Managing design under lump-sum contract. *Journal of Management in Engineering*, *11*(2), 21-25.

[38] Antony, J., Lizarelli, F. L., & Fernandes, M. M. (2021). A Global study into the reasons for Lean Six Sigma project failures: key findings and directions for further research. *IEEE Transactions on Engineering Management*, 1-12.

[39] Wawasi, V. S. Z., & Were, S. (2017). Factors Influencing Performance of Micro, Small and Medium Enterprise Projects in Nairobi City County, Kenya. *European Journal of Business and Strategic Management*, *2*(7), 67-79.

[40] Couillard, J. (1995). The role of project risk in determining project management approach. *Project Management Journal*, *26*, 3-15.

[41] Enshassi, A. (1996). A monitoring and controlling system in managing infrastructure projects: Project planning, monitoring and controlling in the typical socio-economic

background of Gaza Strip; pose special management problems towards achievement of project goals. *Building Research and Information*, *24*(3), 183-189.

[42] Ritz, J.G. (1994). *Total Construction Project Management.* 1st Edition. New York: McGraw Hill Book Company.

[43] Lewis, M. W., Welsh, M. A., Dehler, G. E., & Green, S. G. (2002). Product development tensions: Exploring contrasting styles of project management. *Academy of Management Journal*, *45*(3), 546-564.

[44] Haans, R. F., Pieters, C., & He, Z. L. (2016). Thinking about U: Theorizing and testing U-and inverted U-shaped relationships in strategy research. *Strategic Management Journal*, *37*(7), 1177-1195.

[45] Bonner, J. M., Ruekert, R. W., & Walker Jr, O. C. (2002). Upper management control of new product development projects and project performance. *Journal of Product Innovation Management: An International Publication of the Product Development & Management Association*, *19*(3), 233-245.

[46] Unger, B. N., Kock, A., Gemünden, H. G., & Jonas, D. (2012). Enforcing strategic fit of project portfolios by project termination: An empirical study on senior management involvement. *International Journal of Project Management*, *30*(6), 675-685.

[47] Lee, S., Yun, S., & Srivastava, A. (2013). Evidence for a curvilinear relationship between abusive supervision and creativity in South Korea. *The Leadership Quarterly*, *24*(5), 724-731.

[48] ORSRG. (2021). Operations Research & Scheduling Research Group, Real project data, Last Accessed (02.02.2021): https://www.projectmanagement.ugent.be/research/data/realdata

[49] Adoko, M. T., Mazzuchi, T. A., & Sarkani, S. (2015). Developing a cost overrun predictive model for complex systems development projects. *Project Management Journal*, *46*(6), 111-125.

[50] Locatelli, G., Invernizzi, D. C., & Brookes, N. J. (2017). Project characteristics and performance in Europe: An empirical analysis for large transport infrastructure projects. *Transportation research part A: policy and practice, 98,* 108-122.

[51] StataCorp. (2017). *Stata Statistical Software: Release 15.* College Station, TX: StataCorp LLC.

[52] Wooldridge, J. M. (2016). *Introductory Econometrics: A Modern Approach*. 6th Edition. South-Western Cengage Learning, Ohio, The United States.

[53] Aljohani, A., Ahiaga-Dagbui, D., & Moore, D. (2017). Construction projects cost overrun: What does the literature tell us?. *International Journal of Innovation, Management and Technology*, 8(2), 137.

[54] Bendoly, E., Swink, M., & Simpson III, W. P. (2014). Prioritizing and monitoring concurrent project work: Effects on switching behavior. *Production and Operations Management*, *23*(5), 847-860.

[55] Simpson III, W. P. (2010). Project planning and control when time matters: Focus on process to synchronize and drive results. *Production and Inventory Management Journal*, *46*(2), 26.

[56] Dibachi, F., R. L. Dibachi. 2002. *Just Add Management: Seven Steps to Creating a Productive Workplace and Motivating your Employees in Challenging Times.* McGraw-Hill, New York.

[57] Zhang, J., Jia, S., & Diaz, E. (2018). Dynamic monitoring and control of a critical chain project based on phase buffer allocation. *Journal of the Operational Research Society*, *69*(12), 1966-1977.

[58] Vanhoucke, M. and Colin, J. (2016). On the use of multivariate regression methods for longest path calculations from earned value management observations. *Omega, 61*, 127-140.

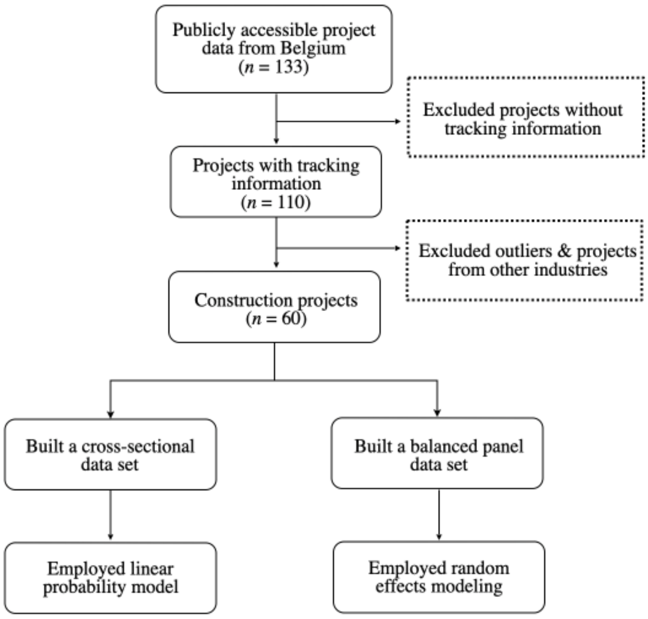
[59] Martens, A., & Vanhoucke, M. (2020). Integrating corrective actions in project time forecasting using exponential smoothing. *Journal of Management in Engineering, 36*(5), 04020044.

[60] Browning, T. R. (2014). A quantitative framework for managing project value, risk, and opportunity. *IEEE Transactions on Engineering Management*, *61*(4), 583-598.

[61] Liu, G., & Yokoyama, S. I. (2015). Proposal for a quantitative skill risk evaluation method using fault tree analysis. *IEEE Transactions on Engineering Management*, *62*(2), 266-279.

Figures

Figure 1: Research Flow chart



Tables

Table 1: Selected Projects for Data Analysis		
Number of Tracking Periods	Number of Projects	Project Codes
4	21	C2013-15, C2013-16, C2016-15, C2016-16, C2016-17, C2016-18, C2016-19, C2016-20, C2016-21, C2016-22, C2016-23, C2016-24, C2016-25, C2016-26, C2016-27, C2016-28, C2016-29, C2016-30, C2016-31, C2016-32, C2016-33
[5, 8]	14	C2011-12, C2013-01, C2013-12, C2013-17, C2015-04, C2015-08, C2015-27, C2015-29, C2015-33, C2015-34, C2016-11, C2016-12, C2016-13, C2016-14
[9,11]	15	C2013-04, C2013-07, C2013-09, C2013-13, C2015-01, C2015-02, C2015-03, C2015-05, C2015-06, C2015-07, C2015-09, C2016-03, C2016-05, C2016-07, C2019-02
[12,16]	10	C2013-08, C2014-05, C2014-07, C2014-08, C2015-30, C2015-32, C2016-01, C2016-02, C2016-04, C2016-06
Source: ORSRG [48].		

Table 2: Variable Descriptions

Dependent Variables	
Late Completion	=1 if Total Actual Duration > Total Planned Duration; =0 Otherwise
Over Budget	=1 if Total Actual Cost > Total Planned Value; =0 Otherwise
Schedule Performance Index (SPI)	=Cumulative Earned Value/Cumulative Planned Value
Cost Performance Index (CPI)	=Cumulative Earned Value/Cumulative Actual Cost
Main Explanatory Variables	
Regular Tracking	=1 if the project is tracked in regular time intervals; =0 Otherwise
Tracking Frequency	=Total Number of Tracking Periods*100/Total Actual Duration
Cumulative Tracking Frequency	=Cumulative Number of Tracking Periods*100/Cumulative Actual Duration
Control Variables	
Total Actual Cost (TAC) Categories	=1 if €25K ≤ Total AC ≤ €250K =2 if €250K< Total AC ≤ €750K =3 if €750K< Total AC ≤ €1.5M =4 if €1.5M < Total AC < €5.5M
Total Actual Duration (TAD) Categories	=1 if 75 Days ≤ Total AD ≤ 100 Days =2 if 100 Days < Total AD ≤ 200 Days =3 if 200 Days < Total AD ≤ 300 Days =4 if 300 Days < Total AD < 600 Days
Other Relevant Variables	
Planned Value (PV)	Planned value of the project for the relevant tracking period in Euros.
Cumulative Planned Value (CPV)	Planned value of the project for the relevant tracking quarter in Euros.
Earned Value (EV)	Earned value of the project for the relevant tracking period in Euros.
Cumulative Earned Value (CEV)	Earned value of the project for the relevant tracking quarter in Euros.
Actual Cost (AC)	Actual cost of the project for the relevant tracking period in Euros.
Cumulative Actual Cost (CAC)	Actual cost of the project for the relevant tracking quarter in Euros.
Total Actual Cost (TAC)	Actual cost of the project at completion in Euros.

Actual Duration (AD)	Actual duration of the project for the relevant tracking period in days.
Cumulative Actual Duration (CAD)	Actual duration of the project for the relevant tracking quarter in days.
Total Actual Duration (TAD)	Actual duration of the project at completion in days.
Tracking Quarter	Quarter of the project time with respect to total actual duration. 1= 1st Quarter; 2=2nd Quarter; 3=3rd Quarter; 4=4th Quarter. For projects with 4 tracking periods, each tracking period is assigned for a quarter. For other projects, total actual duration of the project is divided into 4 and the closest tracking control period is assigned for the corresponding quarter.
Total Number of Tracking Periods	Number of tracking control periods of the project at completion. We consider number of tracking periods when the project achieves 100% completion rate.
Cumulative Number of Tracking Periods	Cumulative number of tracking control periods of the project for the relevant tracking quarter.
Source: ORSRG [48].	

Table 3: Descriptive Statistics for Cross Sectional and Panel Variables

Variables	**N**	**Mean or %**	**Standard Deviation**	**Min**	**Max**
Cross-Section Variables					
Late Completion	60	0.650	0.481	0	1
Over Budget	60	0.733	0.446	0	1
Regular Tracking	60	0.667	0.475	0	1
Total Number of Tracking Periods	60	7.417	3.446	4	14
Tracking Frequency	60	3.999	1.340	1.515	7.692
Total Actual Duration (Days)	60	207.617	117.586	75	569
Total Actual Cost (Euros)	60	943,860.9	1,095,807	25,313.12	5,414,544
Total Actual Duration Categories	60	-	-	-	-
[75, 100]	15	25.00%	-	-	-
(100, 200]	16	26.67%	-	-	-
(200, 300]	19	31.67%	-	-	-

(300, 600)	10	16.67%	-	-	-
Total Actual Cost Categories	60	-	-	-	-
[25K, 250K]	21	35.00%	-	-	-
(250K, 750K]	14	23.33%	-	-	-
(750K, 1.5M]	12	20.00%	-	-	-
(1.5M, 5.5M)	13	21.67%	-	-	-
Panel Variables					
Schedule Performance Index	240	1.252	4.792	0.175	74.925
Cost Performance Index	240	0.955	0.120	0.477	1.568
Cumulative Number of Tracking Periods	240	4.350	3.123	1	14
Cumulative Tracking Frequency	240	3.972	1.797	0.602	16.667
Cumulative Actual Duration	240	125.046	96.859	6	569
Cumulative Actual Cost	240	556,622.7	792,154.7	842.58	5,414,544
Cumulative Earned Value	240	540,860.6	792,760.7	842.58	5,999,600
Cumulative Planned Value	240	602,672.6	859,174	185	5,999,600
Number of Quarters	4	-	-	-	-
Number of Projects	60	-	-	-	-

Source: ORSRG [48].

Table 4: Linear Probability Models of Late Completion

Variables	Model 1	Model 2	Model3	Model 4	Model 5	Model 6
Regular Tracking	-0.375*** (0.105)					-0.256** (0.101)
Tracking Frequency		-0.565 (0.044)	-0.492*** (0.139)			-0.429* (0.217)

Tracking Frequency Square			0.053*** (0.014)			0.0493** (0.0209)
Actual Cost (Euros):						
[25K, 250K]				-0.452*** (0.156)		-0.473*** (0.165)
(250K, 750K]				Base		Base
(750K, 1.5M]				-0.048 (0.159)		0.0466 (0.167)
(1.5M, 5.5M)				0.060 (0.154)		-0.0704 (0.171)
Actual Duration						
[75, 100]					-0.225 (0.181)	-0.0664 (0.146)
(100, 200]					Base	Base
(200, 300]					0.112 (0.163)	-0.0257 (0.159)
(300, 600)					0.275* (0.159)	-0.203 (0.225)
Intercept	0.900*** (0.068)	0.876*** (0.170)	1.670*** (0.297)	0.786*** (0.114)	0.625*** (0.125)	1.889*** (0.521)
Observations	60	60	60	60	60	60
R-squared	0.137	0.024	0.113	0.239	0.126	0.390
F-statistic	12.66***	1.66	6.94***	5.28***	3.29**	6.67***
Notes: Robust standard errors in parentheses. ***p<0.01 **p<0.05 *p< 0.10. Source: ORSRG [48].						

Table 5: Linear Probability Models of Over Budget

Variables	**Model 1**	**Model 2**	**Model3**	**Model 4**	**Model 5**	**Model 6**
Regular Tracking	-0.025 (0.122)					0.0774 (0.159)
Tracking Frequency		-0.045 (0.041)	-0.203 (0.136)			-0.384* (0.222)

Tracking Frequency Square			0.019 (0.157)			0.0335 (0.0232)
Actual Cost (Euros):						
[25K, 250K]				0.071 (0.138)		-0.0541 (0.142)
(250K, 750K]				Base		Base
(750K, 1.5M]				-0.286 (0.188)		-0.268 (0.189)
(1.5M, 5.5M)				-0.093 (0.174)		-0.0969 (0.178)
Actual Duration						
[75, 100]					0.246* (0.137)	0.315** (0.157)
(100, 200]					Base	Base
(200, 300]					-0.109 (0.168)	-0.0577 (0.162)
(300, 600)					0.113 (0.178)	-0.100 (0.252)
Intercept	0.750*** (0.098)	0.913*** (0.162)	1.202*** (0.272)	0.786*** (0.114)	0.688*** (0.120)	1.674*** (0.477)
Observations	60	60	60	60	60	60
R-squared	0.001	0.018	0.032	0.089	0.096	0.212
F-statistic	0.04	1.21	1.41	1.61	2.78**	1.72

Table 6: Random Effects Panel Models of Schedule Performance Index (SPI) and Cost Performance Index (CPI)

Variables	**Model 1 (SPI)**	**Model 2 (SPI)**	**Model 3 (SPI)**	**Model 4 (CPI)**	**Model 5 (CPI)**	**Model 6 (CPI)**
Lag of Cost Performance Index				0.474*** (0.0669)	0.443*** (0.0727)	0.428*** (0.0691)
Lag of Schedule Performance Index	0.0454*** (0.00258)	0.0456*** (0.00273)	0.0454*** (0.00273)			
Regular Tracking	0.0474 (0.0448)		-0.0156 (0.0493)	-0.0174 (0.0211)		-0.0374 (0.0233)

Cumulative Tracking Frequency		0.160*** (0.0485)	0.168*** (0.0511)		0.0371** (0.0170)	0.0541** (0.0215)
Cumulative Tracking Frequency Square		-0.0143*** (0.00399)	-0.0151*** (0.00453)		-0.00494*** (0.00181)	-0.00662*** (0.00229)
Actual Cost (Euros):						
[25K, 250K]	-0.0416 (0.153)	-0.0131 (0.150)	-0.0132 (0.151)	-0.00915 (0.0233)	-0.00419 (0.0257)	-0.00376 (0.0255)
(250K, 750K]	Base	Base	Base	Base	Base	Base
(750K, 1.5M]	-0.0879 (0.113)	-0.100 (0.113)	-0.102 (0.113)	-0.0112 (0.0216)	-0.0126 (0.0220)	-0.0143 (0.0236)
(1.5M, 5.5M)	-0.0276 (0.104)	-0.0274 (0.102)	-0.0284 (0.102)	-0.00748 (0.0196)	-0.00527 (0.0223)	-0.00635 (0.0210)
Actual Duration						
[75, 100]	0.0702 (0.130)	0.0463 (0.121)	0.0470 (0.122)	-0.0174 (0.0282)	-0.0138 (0.0277)	-0.0140 (0.0283)
(100, 200]	Base	Base	Base	Base	Base	Base
(200, 300]	-0.00618 (0.0527)	-0.00906 (0.0518)	-0.0109 (0.0535)	-0.00994 (0.0205)	-0.00329 (0.0224)	-0.00783 (0.0223)
(300, 600)	-0.0971* (0.0580)	0.00446 (0.0477)	-0.000753 (0.0530)	-0.0485* (0.0292)	-0.0268 (0.0253)	-0.0425 (0.0287)
Constant	0.925*** (0.0991)	0.563*** (0.131)	0.558*** (0.130)	0.548*** (0.0743)	0.498*** (0.0812)	0.505*** (0.0786)
Observations	180	180	180	180	180	180
Number of Projects	60	60	60	60	60	60
Overall R-squared	0.550	0.563	0.563	0.013	0.441	0.449
Wald Chi-Square	37711.8***	46918.4***	47431.0***	1.57	200.61***	247.47***
Notes: Robust standard errors in parentheses. ***p<0.01 **p<0.05 *p< 0.10 Source: ORSRG [48].						

Table 7: Hypothesis Testing Results

	Cross-Sectional Data Findings	***Panel Data Findings***	***Cross-Sectional Data Findings***	***Panel Data Findings***
	Late Completion	*SPI*	*Budget Overrun*	*CPI*
Regular Tracking	Hypothesis 1a: Supported	Hypothesis 1b: Not Supported	Hypothesis 2a: Not Supported	Hypothesis 2b: Not Supported
Tracking Frequency Indicator	Hypothesis 3a: Supported	Hypothesis 3b: Supported	Hypothesis 4a: Not Supported	Hypothesis 4b: Supported

Appendix:

Table: Probit Models for Late Completion and Over Budget

Variables	**Late Completion**	**Over Budget**
Regular Tracking	-0.932** (0.448)	0.398 (0.510)
Tracking Frequency	-2.026* (1.132)	-1.624* (0.898)
Tracking Frequency Square	0.240* (0.132)	0.145 (0.0914)
Actual Cost (Euros):		
[25K, 250K]	-1.554*** (0.556)	-0.221 (0.550)
(250K, 750K]	Base	Base
(750K, 1.5M]	0.306 (0.584)	-0.911* (0.545)
(1.5M, 5.5M)	-0.0661 (0.656)	-0.399 (0.576)
Actual Duration		
[75, 100]	-0.275 (0.504)	1.288** (0.648)
(100, 200]	Base	Base
(200, 300]	-0.351 (0.568)	-0.0535 (0.479)
(300, 600)	-0.951 (1.003)	-0.238 (0.813)
Intercept	5.843** (2.582)	4.530** (2.028)
Observations	60	60

Pseudo R-squared	0.347	0.203
Wald Chi-square-statistic	23.30*	12.25
Notes: Robust standard errors in parentheses. ***p<0.01 **p<0.05 *p< 0.10. Source: ORSRG (2021).		

Figure: A project example

OR-AS Operations Research Applications and Solutions	Case Name: **Office Finishing Works (5)**	Sector	Construction (Commercial Building)
	OR-AS Operations Research - Applications and Solutions www.or-as.be info@or-as.be	Baseline Schedule	Schedule with resources
			Schedule with costs
		Risk Analysis	Random simulation
			One of nine std. scenarios
Submitted by	N/A		User defined distributions
Date	August 7, 2013	Project Control	Automatic tracking
File Name	C2013-17 Office Finishing Works (5).p2x		Tracking based on user input

1. Project description

Project authenticity

The finishing works inside an office building, comprising the interior joinery and the placement of plaster walls, partition walls (also acoustic), raised floors, suspended ceilings, and furniture.

The project consists of activity and cost data that were obtained directly from the actual project owner.

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