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The Impact of Uncertainty in the Measurement of Progress in Earned Value Analysis

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Abstract

Earned value management (EVM) is a project management methodology that integrates scope, cost and time, and requires the periodic measurement of cost and work performed. It is supported by a quantitative technique, earned value analysis (EVA), to evaluate project's performance and to forecast its final results thru the monitoring of: planned value (PV), earned value (EV) and actual cost (AC). In EVA, the EV of an activity represents the amount of work performed in a period and, if defined as the product of percent complete (PC) by PV, it represents the project's progress. Thus, the error associated with EV may result from the uncertainty in any of those values.

Although the uncertainty with PV has been widely discussed, the impact of the uncertainty associated with progress measurement has not. Progress is hard to measure, especially in an integrated vision of scope, cost and time. It results from people's judgment and, therefore, it comprises uncertainty. Nevertheless, EV is a deterministic measurement technique.

This paper intends to contribute for this discussion by evaluating the error in EV driven by the uncertainty of progress measurement, with a *ceteris paribus* analysis of the PC of activities, and its impact on EVA performance metrics.

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(1)

 $EV = PC \times PV$

Keywords: Earned Value; Progress Measurement; Progress Control; Percent Complete; Percentage of Completion Method; Panel Data.

1. Introduction

EVM is a powerful methodology to manage project's scope, time and cost. It provides, early on, indicators of the expected results for the project, based on its past performance, and highlights the need for corrective actions, allowing the project manager to adjust his strategy according to the intended objectives [1]. EVA compares the performance measurement baseline to the actual schedule and cost performance by monitoring three key dimensions: PV, EV and AC. EV is often used to determine the PC [2]:

During the development of a project, at any time, some activities are completed (i.e. 100% complete), some activities have not yet started (i.e. 0% complete) and other activities have already started but have not yet been completed, and it is for the latter group that it is necessary to estimate the PC [3]. For any intermediate point the PC is more or less arbitrated [4].

Realistically determine the progress of work packages is usually difficult but essential to ensure that EVA is accurate and meaningful [5]. One can measure the work performed and compared it with the work planned. Likewise, one can measure the money spent and compared it with the forecast. But one can't easily measure the progress in an integrated view, taking into account the triple constraint of cost, time and scope [6]. Another problem for measuring progress arises from pressure from management to influence reported results, in order to ensure certain results [5].

Despite the uncertainty associated with the progress of the activities, the EV is considered deterministic in all techniques for its determination when, in reality, the data about the activities come from the judgment of the people and, consequently, carry a certain degree of uncertainty [7].

Although mentioned, this uncertainty has not been properly studied, once only a few recommendations were found in literature, such has [8], [5], [9], [7], [10], [6], [7], [3], [4], [11].

2. Literature review

EV is the essential variable of the EVM system and the measurement of progress should be determined by objective and verifiable criteria [9, 12]. The EV is the measurement of the work done and the photograph of the progress of the work at a certain point of time. Methods for measuring progress should be selected during project planning prior to the start of work and form the basis for measuring progress during project implementation [11]. The main objective in choosing the method of performance measurement is to have the most objective, accurate and timely evaluation possible of the work performed and the time and costs spent [11].

The EV is defined by the status of the activities of each work package, and the method for determining it depends on the type of work to perform. In the context of EVM, there are two basic classifications for the nature of the works: discrete and level of effort (LOE). The discrete work is related to the development of products and services that can be directly planned, timed and measured. LOE is a general, or supportive, effort that does not lead to a clear end [13].

In order to select the appropriate method, several aspects should be considered, namely: the characteristics of the work (duration and measurability), the requirements, the units of measure, the risk and the accuracy of the measurement. The key points associated with each method are described in detail in the PMI[11]. Since the type of work can vary within the same project, there is no suitable single method for reporting progress. The methods presented, or the combination of those, can be grouped into quantitative and qualitative[5, 9].

The main objective is to obtain the most objective, accurate and timely evaluation of the work, time and cost possible. Incorrect choice of method may result in incorrect situation points and, consequently, inappropriate management actions [11].

There is little doubt that accurate data collection is one of the most problematic aspects of EVM[9]. The criteria for measuring progress, to measure the work performed, must be established for each work package, part of the work breakdown structure (WBS) [2]. Determining the PC is a complex and often misunderstood issue. Because it is possible to determine it by different methods, the prior definition of the method to be used increases the meaning of

the results[14]. Progress measurement shall be carried out in accordance with the method defined in the planning by the Project Manager, who shall have the capacity to carry out this measurement [15].

The output is just as good as the input which is certainly a concern when the attribution of values is more subjective than objective. In the EVM, this occurs when the EV is assigned to an activity, or work package, with methods such as the PC, when there may be ambiguity in assigning progress. The project manager must struggle to have as objective data as possible and minimize the occurrence, or relative weight, of subjective assessments [10].

Of the possible techniques for measuring EV, the PC is the simplest and most widely used, however it has the disadvantage of using subjective judgments to describe the percentage of complete work.[7]. This technique, where in each period an estimate of the complete percentage of each activity is made, manages to be the most subjective of all techniques to determine the EV, if there are no objective indicators to support the estimate. This leads to errors and uncertainties that result in biased judgments, when the total work required to perform a given activity is unknown, or uncertain, and is outside the control of the project manager.

Another problem for measuring progress arises from management pressure to influence the reported results, both to ensure certain results and to avoid "bad news", in the expectation that performance problems will change [5]. Values can be distorted by optimistic perspectives at the beginning of a task, when they are eager to show progress, or by a pessimistic perspective at the end, as the complexity of the task is better understood [10]. If progress is consistently reported by excess in the early stages, the mistake will be obvious due to the lack of progress in the final stages [4].

Quantitative techniques for measuring project progress are obviously better than qualitative (subjective) techniques. Measuring progress is an estimate and does not justify spending too much time trying to get an exact value, especially for small work packages. Instead, attention should be dedicated to the most valuable work packages. The errors inherent in each work package tend to cancel out as progress values are aggregated at the project [5]. For projects with few activities, rough measurements of progress can be misleading. However, in projects with a significant number of activities, the error caused by the estimate associated with small parts of the project (relative to the total amount of time/cost) make the error negligible [3].

The weakest link in EV calculation is determining the PC[4]. The difficulty in performing analyses stems from the difficulty in predicting the PC, which, in addition to being arbitrary, and not a simple task, should be applied individually to each activity, and not to the overall project. Estimating the percentage of completion of a project without carefully studying each of its activities is not wise [3]. The tendency to accurately estimate the completion state of a project, for example 73% completion, does not have, in most cases, real meaning. The task of estimating is difficult and arbitrary, which is why rule 50/50, and similar ones, are adopted. For detailed, small and short-term work, rules 50/50 and 25/75 are usual and effective [11]. Rule 50/50 is too generous at the beginning of activities and conservative near the end, tending to balance itself from a global perspective.[3]. When an activity starts it is assigned 50% completion and when it ends 100%. If the work packages are small (less than 50 hours), this method will work well [4]. "Fixed formula" methods are usually used in short-term work packages but can easily be used in complex projects when repetitive tasks occur. When used in many tasks within a control account, the average of "fixed formula" evaluations makes this method reasonable [10]. The error in the total EV of the project, associated with the use of rules to credit the EV of each individual activity, tends to reduce as the project develops. These rules are suitable for activities whose duration does not exceed three reporting periods and there are several simultaneous activities [9].

3. Methodology

This study intends to evaluate, in a real-life context, the error of the EVA metrics originated by the uncertainty in the measurement of the project's progress, keeping all the remaining variables constant, that is, with a *ceteris paribus* analysis of the PC. For this purpose, several real-life projects are analyzed, following a Multiple Case Study methodology [16], to draw conclusions and increase the reliability of the analysis. The projects used are described in section 3.1 and the measurement of progress is made as described in section 3.2.

The study follows a quantitative approach. In a first phase, the EV error, associated with the uncertainty in measuring progress, is analysed through the statistical description of Mean Absolute Percentage Error (MAPE), as per point 3.3. In a second phase, the influence of the time and cost planning characteristics of the project on the error is evaluated using methods for Panel Data (Panel Data Model), according to point 3.4.

3.1. Real-life project database

This study used the database of real projects located in http://www.or-as.be/research/database [17, 18]. At the date of the study, the database had 125 projects (C2011-01 to C2016-24), of which 23 had no progress measurement. To guarantee the completeness and representativeness of the sample, only the 23 projects whose authenticity as a reallife project was confirmed by Batselier and Vanhoucke [19] were considered. Of these, to ensure homogeneous results and avoid distortion, projects whose time intervals between tracking periods (TP) are not constant were excluded. In order to control the amplitude of the error, in all activities whose duration extends for more than 3 TP, the real progress values were adopted. The 15 real projects that are described in Table 1 were selected and 332 TP were analyzed, of which 185 had activities in execution (0 < PC < 100).

	Project		Activities	(**)	1	Fracking Po	eriods		
Code	Name	Duration (*) [days]	BAC [€]	Total [un]	Duration (*) [days]	D > 3TP (***)	Qt. [un]	x ⁻ [days]	0 <pc<100 [un]</pc<100
C2011-07	Patient Transport System	539	180.759,44	49	[1;97]	-	23	28	5
C2011-13	Wind Farm	723	21.369.835,51	100	[1;245]	12	120	7	49
C2012-13	Pumping Station Jabbeke	171	336.410,15	74	[0;32]	-	28	7	13
C2013-01	Wiedauwkaai Fenders	211	1.069.532,42	39	[1;211]	2	6	30	5
C2013-02	Sewage Plant Hove	554	1.236.603,66	123	[1;549]	1	17	30	10
C2013-05	PET Packaging	719	874.554,28	28	[29;661]	9	31	30	18
C2013-06	Government Office Building	547	19.429.810,51	273	[2;251]	2	18	30	17
C2013-07	Family Residence	282	180.476,47	46	[1;49]	-	11	29	5
C2013-13	Office Finishing Works (1)	326	1.118.496,59	11	[1;150]	2	9	30	7
C2013-15	Office Finishing Works (3)	235	341.468,11	16	[4;134]	1	6	30	3
C2013-16	Office Finishing Works (4)	269	248.203,92	5	[22;125]	-	5	30	3
C2013-17	Office Finishing Works (5)	221	244.205,40	22	[1;207]	1	5	30	3
C2014-01	Mixed-use Building	735	38.697.822,73	41	[7;295]	8	24	30	20
C2014-02	Playing Cards	171	191.492,70	21	[1;69]	3	29	7	15
C2014-03	Organizational Development	315	43.170,15	111	[1;52]	-	13	28	12

Table 1. Description of real-life projects analyzed

(*) calendar days. (**) Activities costing more than 1 €. (***) Number of activities lasting more than 3 Tracking Periods (D > 3TP).

3.2. Progress Measurement

In the study, progress was estimated using the "fixed formula" method, with the aim of analyzing the error caused by an incorrect measurement of progress. It is assumed that the cumulative cost profile versus time in projects takes the shape of an S curve [20], so, in order to guarantee a better adherence between the real and the estimated EV curve and, thus, control the amplitude of the error, the projects were divided into three stages of completion, depending on the elapsed time: $0\% \le t < 30\%$ refers to early stage, $30\% \le t < 70\%$ refers to middle stage and $70\% \le t \le 100\%$ refers to late stage.

3.3. EV Error and the most Adjusted Rule

The "fixed formula" method was adopted with rules 0/100, 10/90, 25/75, 50/50 e 75/25. In Table 2 the descriptive statistics of the MAPE between the estimated and the real EV, obtained for each rule, in each TP of each project, is presented. Based on the results, the rule with the best fit for each project and status of completion is identified, that is, the rule to which the lowest MAPE corresponds. The MAPE was calculated according to the following formula:

$$MAPE = \frac{100\%}{n} \times \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|, \text{ were } A_t \text{ is the real value and } F_t \text{ is the estimated value}$$
(2)

3.4. Influence of Project Planning Features

The influence of project's time and cost planning characteristics was studied with linear models using appropriate methods for Panel Data, with unbalanced panel – the projects have a different number of observations over time [21] – and fixed in the number of projects – the same projects were observed over time [22], with Stata software [23].

The variables were chosen based on the analysis of the simple correlation matrix. Cross-sectional Data are the set of observations of distinct individuals, or units, at a given moment in time [24] and the Panel Data contains the measurement of these units in various periods of time [24]. The use of several observations of the same units over time allows causality to be inferred in situations where it would be very difficult if only individual observations existed [21]. These methods allow to analyse the effect of explanatory variables within each project and between projects, removing, in some methods, the unobserved effect and eliminating the possible bias caused by particular context characteristics of each project [21].

Considering the sets of observations obtained for the "fixed formula" method with the best fit, for each project and status of completion, i.e. the lowest MAPE, several methods were applied to the Panel Data to evaluate the statistical significance and influence of each explanatory variable associated with the project's time and cost planning characteristics on the errors obtained. The following methodologies were adopted to estimate the linear model:

- 1. Ordinary Least Squares (OLS) method applied to the 185 observations through Pooled OLS Estimation (POLS), admitting that the cross-section data set for each TP of each project are independent and that the unobserved group effects are not correlated with the explanatory variables for each observation associated to each TP [21]. The use of Pooled Cross Sections allows us to verify how a given relationship varies between successive observations [21];
- 2. *Random Effects Model* (RE) method, assuming that the *cross-section data set* for each TP of each project are independent and that the unobserved group effects are not correlated with the explanatory variables for each observation [21];
- 3. *Fixed Effects Model* (FE) method, assuming that the *cross-section data set* for each TP of each project are independent and that the unobserved group effects are arbitrarily correlated with the explanatory variables for each observation [21].

Within each project, the observed results may be correlated, so each project constitutes a *Cluster*. Thus, the analyses were repeated with the robust estimation of standard errors, admitting the existence of unobserved effects common to the observations within each project (*Cluster effect*), correcting the standard error and, consequently, the statistical significance of the explanatory variables with the robust estimator per *Cluster* (which corrects heteroskedasticity and within autocorrelation) [21].

The explanatory variables analyzed can be aggregated into two groups: the primary explanatory variables and the secondary explanatory variables, which result from the quotient between primary explanatory variables. Appendix A describes the project's time and cost planning characteristics adopted as possible explanatory variables.

R-Squared defines the percentage of the total variation in the sample of the dependent variable that is explained by the model [21]. This *goodness-of-fit* increases whenever new explanatory variables are added to the model, which makes *R-Squared* inappropriate to decide whether a given variable should be added [21]. Adding irrelevant variables does not bias the estimation of the model but increases the variance of the of the coefficient's estimator for the remaining variables. On the other hand, the exclusion of relevant variables can make the model biased [21]. A model with too many irrelevant variables can lead to a loss of efficiency in the coefficient estimator and, therefore, to less accurate estimates [24]. The option of incorporating a variable into the model was based on its statistical significance, i.e. the analysis of its influence on bias and variance [21].

To identify the irrelevant variables on the model, the following iterative procedure was adopted: for each dependent variable, three initial linear models (POLS, RE and FE) were constructed ("Initial Model"), with all explanatory variables. When in the model obtained there were variables without statistical significance (p-value > 0.05), in the following iteration the one that presented the highest p-value was eliminated. The procedure was repeated until all explanatory variables of the model had statistical significance, or until all variables were eliminated. After the

elimination of the second irrelevant variable, in each iteration the *F-test* of joint significance of the eliminated variables was performed [21] in order to ensure that only variables that did not have isolated or joint statistical significance were eliminated (p-value > 0.05). From the previous process, 3 "Individual Final Models" (POLS, RE and FE) resulted for each dependent variable. From these models, for each dependent variable, a unique "Intermediate Model" was constructed, consisting of the independent variables resulting from the 3 "Individual Final Models". To select the most appropriate model to build the "Final Model", the methodology suggested by Park [25], based on *F-test, Breusch-Pagan Lagrange multiplier* (LM) *test* and *Hausman test*, was adopted. The previously described procedure for constructing the "Final Model" for each dependent variable is represented in Figure 1:

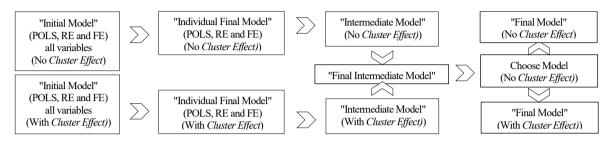


Figure 1 Procedure to build the Final Model

4. Results and Discussion

4.1. Error caused by Uncertainty in Measuring Progress

The EV for the real progress and its estimation, i.e. the EV_{Real} and $EV_{Estimate}$, were determined by the following expressions:

$$(3) \quad EV_{Real} = PC_{Real} \times PV \qquad (4) \quad EV_{Estimate} = PC_{Estimate} \times PV$$

To determine the earned schedule (ES), the PV curve was determined by linear interpolation of the sets (Date; PV) of the project's TPs. For each project, the MAPE was calculated for the EV error, for each phase and for each "fixed formula" rule, in all TPs with running activities (AE). Table 2 summarizes the number of projects and TPs where each estimation rule was the most adjusted (lowest MAPE), by phase and by project.

4	Rule	Qt. l	Proj.	Qt.	ТР	1	Rule	Qt. Proj.		Qt. TP	
t	Kule	[un]	[%]	[un]	[%]	t	Kule	[un]	[%]	[un]	[%]
	0/100	0	0,00	0	0,00		0/100			1	0,54
	10/90	0	0,00	0	0,00			0	0,00		
$0\% \ge t < 30\%$	25/75	6	42,86	14	31,82						
	50/50	6	42,86	25	56,82		10/90				1
	75/25	2	14,29	5	11,36			0	0,00	1	0,54
	0/100	0	0,00	0	0,00						
	10/90	1	7,69	1	2,04						
$30\% \ge t < 70\%$	25/75	0	0,00	0	0,00	$0\% \ge t \le 100\%$	25/75	4	26,67	22	11,89
	50/50	10	76,92	44	89,80						
	75/25	2	15,38	4	8,16		50/50			136	73,51
	0/100	1	8,33	1	1,09			9	60,00		
	10/90	0	0,00	0	0,00						
$70\% \ge t \le 100\%$	25/75	1	8,33	8	8,70						
	50/50	6	50,00	67	72,83		75/25	2	13,33	25	13,51
	75/25	4	33,33	16	17,39						

Table 2 Most adjusted (lowest MAPE) estimation rule, by phase and overall project

Considering the most adjusted rule to each phase of each project, Table 3 presents statistical description of errors in the TPs with running activities. In the scope of this study (*ceteris paribus* analysis of PC), the EV error is equal to the PC error, schedule performance index (SPI) error and cost performance index (CPI) error, since, in each TP, the only variable is the EV and the PV and AC are constants. For the same reason, the ES error is equal to the SPI(t) error.

TP [un]	Var.	EV/PC/SPI/CPI	sv	CV	ES/SPI(t)	SV(t)
185	\bar{x}	3,01	23,71	40,89	2,59	19,98
165	S	7,42	106,15	200,72	6,61	69,97

Table 3 Statistical description of errors (MAPE [%]) considering the most adjusted rule to each phase of each project

4.2. Factors influencing error

For the *Panel Data* associated with the most adjusted rule, the correlation matrix between variables was determined. It is verified that the error in the EV has a moderate correlation with the relative PV of the running activities (costAE_BAC), weak correlation with the duration (absolute and relative) and with the relative amount of the activities in execution (durAE, durAE, durTOTAL and noAE_noTOTAL) and negligible correlation with the other variables. All correlations are positive. Correlations with the same variables were identified SV error and, with the exception for absolute duration of the running activities, also for the SV(t) error. The CV error showed negligible correlations with all explanatory variables.

In order not to make this explanation exhaustive, only the results obtained for the EV error are described in this paper in detail. For EV error, statistical significance was identified for the total number of activities (noTOTAL), for the number of TP (noTP), for the average PV (by activity and duration) of the activities (BAC_noTOTAL and BAC_durTOTAL) and for the relative quantity and cost (noAE_noTOTAL and costAE_BAC) of the activities in execution. In the *Cluster robust* model, statistical significance was also identified for the total duration of the project (durTOTAL). All variables with individual or joint statistical significance in the final models were considered.

For the EV error, the increase in the number of activities (noTOTAL), in the number of TP (noTP), in the average PV of the activities (BAC_noTOTAL), in the relative quantity of activities in progress (noAE_noTOTAL) and in the cost of the activities in execution (costAE) reduces the EV error. On the other hand, the increase in the duration of the total project activities (durTOTAL), in the average daily PV of the activities (BAC_durPROJ) and in the relative cost of the activities in execution (costAE BAC) increases the error of the EV.

The obtained coefficients estimate the impact in the explained variable of a unit variation of the explanatory variables, keeping all the rest constant (ceteris paribus). As an example, for the model with robust estimation of standard errors, for each increase of $1M \in$ in the average PV of activities, a reduction in EV error of 24.440 pp is expected, and for each increase of $1M \in$ in the daily average PV of activities, an increase in EV error of 1751.199 pp is expected. It should be noted that the coefficients obtained should not be directly compared to each other. However, the coefficients can be compared between different dependent variables, allowing to assess their relative impact. Table 4 summarizes the coefficients obtained in the "Final Model" for each error.

		no Cluster Effect				with Cluster Effect					
	EV/PC SPI/CPI (POLS)	SV (RE)	CV (POLS)	ES/SPI(t) (POLS)	SV(t) (FE)	EV/PC SPI/CPI (POLS)	SV (RE)	CV (POLS)	ES/SPI(t) (POLS)	SV(t) (FE)	
noTOTAL	-0,029	0,787	(IOLS)	(IOLS)	(11)	-0,040	1,024	(IOLS)	(IOLS)	(11)	
noTP	-0,155	2,478	4,576			-0,194	3,176	6,300			
durPROJ		-21,933	-33,517				-18,094				
durTOTAL		3,544	4,764			0,054	1,532	-1,670			
BAC			-69,929	-0,745				-82,711	-0,745		
BAC_noTOTAL	-17,852		563,705	8,688		-24,440		574,407	8,688		
BAC_noTP		790,756	919,408				941,890	1221,086			
BAC_durPROJ		-35395,930		438,020		29,276	-40762,750		438,020		
BAC_durTOTAL	1343,234	48916,380	60758,690			1751,199	51899,140	55145,880			

Table 4 Coefficients of Explanatory variables versus Dependent variables

		no Cluster Effect					with Cluster Effect					
	EV/PC SPI/CPI (POLS)	SV (RE)	CV (POLS)	ES/SPI(t) (POLS)	SV(t) (FE)	EV/PC SPI/CPI (POLS)	SV (RE)	CV (POLS)	ES/SPI(t) (POLS)	SV(t) (FE)		
noAE												
noAE_noTOTAL	-0,287	4,542	-12,920	-0,428		-0,328	6,831	-10,533	-0,428			
costAE				-2,183		-1,781			-2,183			
costAE_BAC	0,481		9,271	0,520		0,521		11,191	0,520			
costAE_noAE			-48,606									
durAE		-25,146	-38,830				-23,944					
durAE_durTOTAL		2,792	6,406		2,033					2,033		
durAE_noAE							61,144					

In the FE model for the SV (t) error, no statistically significant relationships were identified with any of the explanatory variables. However, in the POLS and RE model, statistical significance was identified with the same variables as the SV error. No statistically significant relationships were identified between the absolute number of activities in simultaneous execution (noAE) and any of the dependent variables. The most sensitive errors, to the explanatory variables, are the CV and the SV and the least sensitive are the EV/PC/SPI/CPI and the ES/SPI(t).

The increase in the relative PV of the activities in execution (costAE_BAC) and the PV per unit of total duration of the project activities (BAC_durTOTAL) translates into an increase in the error of all EVA metrics.

In a *ceteris paribus* analysis, increasing the total number of activities reduces the error of the EV. However, in reality, this increase will translate into a reduction in the average cost of activities and in the percentage of activities in progress, resulting in an increase in EV error.

The total number of activities has a positive correlation with the BAC, so the increase in one translates into the increase in the other. Thus, on the one hand, the increase in BAC results in an increase in the average PV per activity, which reduces the error of the EV. On the other hand, it also causes an increase in the average PV per unit of total duration, which increases the error of the EV, and it is not clear whether the increase in BAC is favorable or not. On the other hand, the increase in BAC aggravates the error of the remaining EVA metrics.

To circumvent this difficulty, for each primary explanatory variable, a "composite coefficient" was calculated that results from the sum of the coefficient of the primary explanatory variable with the coefficients of the secondary explanatory variables associated with it multiplied by the variation caused by the primary explanatory variable. For example, the addition of an activity to the project (noTOTAL) corresponds to the coefficient composed of:

$$Coef_{noTOTAL_{i}}^{COMPOSITE} = Coef_{noTOTAL_{i}} + Coef_{BAC_noTOTAL_{i}} \times \left(\frac{BAC}{noTOTAL_{i}} - \frac{BAC}{noTOTAL_{i}}\right) + Coef_{noAE_noTOTAL_{i}} \times \left(\frac{noAE}{noTOTAL_{i}} - \frac{BAC}{noTOTAL_{i}}\right)$$

In the expression, the coefficients correspond to the unit variation of the respective explanatory variable in a *ceteris paribus* analysis of the dependent variable *i*, taking as value for the primary explanatory variables the average of the observations of the analyzed projects. Also, in the composite analysis, the most sensitive errors are SV and CV errors, especially to the duration of the project, for the CV error, and the total duration of the activities and to the BAC, for both errors.

BAC is the independent variable with the greatest relative impact in all independent variables and whose increase aggravates all errors, except for the SV error, which it reduces. Increasing the total number of project activities and the duration of the project substantially increases the SV error and reduces all others. The increase in the number of TP reduces all EVA errors.

No statistically significant relationship was identified between the absolute number of activities in progress and any dependent variable. However, in the composite analysis, increasing the number of activities in progress reduces the error of EV and ES. For the SV and CV error, the consequence of increasing in the number of activities in execution is not consistent for the model with and without robust estimation of standard errors.

In the graphical analysis of the dependent variables, all errors decrease throughout the development of the projects.

The coefficients of the explanatory variables depend on the quantity and explanatory variables adopted in the model, that is, adopting other, or new, variables, other coefficients are obtained. Thus, the relative value between the coefficients of the explanatory variables is more relevant than its absolute value.

5. Conclusions

This study evaluated, in a real context, the impact on EVA metrics originated by uncertainty in the measurement of project progress, keeping all other variables constant, that is, with a *ceteris paribus* analysis of the PC. It followed a quantitative methodology, by analyzing several real projects, in which uncertainty in progress was, in a simplified way, estimated with five "fixed formula" rules. For each rule, the MAPE (2) was determined between the actual and estimated EV and, for the most adjusted rule to the actual progress of each project, that is, with the lowest MAPE, the error in EVA metrics was determined. For the results obtained with the most adjusted rule, the influence of the project time and cost planning characteristics, on the various errors, was evaluated through Panel Data methods.

The study sought to evaluate the impact of uncertainty in the measurement of progress (PC) on EV and on EVA's ability to control and forecast (PC_{TOTAL}, CV, SV, SV(t), CPI, SPI and SPI(t)). It was found that the uncertainty in the measurement of progress resulted in a significant EV error that, for the analyzed projects, reached maximum mean values of 81.79% and absolute values of 298,17% (C2013-16). The 50/50 rule was the one that obtained the best adherence to the real curve of progress, for any degree of execution and especially from 30%, having obtained the lowest MAPE value of the EV error in 60% of the projects and in 73.51% of the TPs.

Despite the uncertainty associated with determining the real progress of the project, it is admitted that the Project Manager is able, in most situations, to define whether an activity is 10% or 50% complete, although the same is not necessarily true for small differences, such as defining whether an activity is 10% or 15% complete. To evaluate the error associated with small uncertainties in the measurement of progress, for the most adjusted rule to each project, that is, with the lowest MAPE of the EV error in each phase, the respective EVA metrics were calculated. Mean EV errors of 3.01%, mean CV errors of 40.89% and mean SV(t) errors of 19.98% were obtained. In the scope of this study, the error of the EV is equal to the error of the PC, the SPI and the CPI and the ES(t) error is equal to the error of the SPI(t). This result confirms that there is a significant impact of uncertainty on the measurement of progress on the EV and on the EVA's ability to control and forecast.

The study evaluated the influence of project time and cost planning characteristics on the errors of EV, PC_{TOTAL} , CV, SV, SV(t), CPI, SPI and SPI(t) derived from the uncertainty in measuring progress. Among the modeled project time and cost planning characteristics, the relative cost of running activities recorded statistical significance in all models for EV and ES error. The same was true with the relative number of activities running, for the SV error, and the relative duration of the running activities, for the SV(t) error. For the CV error, no explanatory variables with statistical significance, common to the various models, were identified. The relative amount of activities in execution was the variable with statistical significance in more models, which leads to conclude by its importance in the errors studied. The relative amount of activities running, in number, cost or duration were the project time and cost planning characteristics that most influenced EVA errors.

To determine the project time and cost planning features with the greatest relative impact on EV, PC_{TOTAL}, CV, SV, SV(t), CPI, SPI and SPI(t) error derived from the uncertainty in the measurement of progress, primary explanatory variables and secondary explanatory variables were analyzed, resulting from the quotient between primary explanatory variables.

Regarding the characteristics, it is concluded that projects with higher BAC and shorter duration are the ones with the highest errors. These projects have higher execution rates and therefore should be more carefully planned by the project manager. To mitigate errors, the interval between TP should be as short as possible. The increase in the number of WBS activities, the duration, the number and, above all, the cost of the running activities also contribute to the reduction of errors. It follows from this that the reduction in the duration of the project by recourse to *fast tracking* is preferable in relation to the reduction of the duration of activities by *crashing*, notwithstanding the risk associated with any of these techniques [2]. It should be noted that the most sensitive errors to the uncertainty in the PC are the CV and the SV, which, combined with the great amplitude recorded in them, justifies special attention in its analysis.

The study confirms that the errors caused by the measurement of progress decrease over time, which can be explained by the reduction of uncertainty with the increasing amount of work performed, in cost and time, as indicated by Webb[9] and Lukas [5]. Further confirms that the error decreases with the increasing amount of running activities, as suggested by Norton, Brennan and Mueller [10]. To mitigate the impact of inaccuracy of PC reports on the various EVA metrics, the study identifies a set of planning characteristics to be considered:

- If the "fixed formula" method is adopted in the measurement of progress, and there is no prior experience of the rule to be adopted, rule 50/50 should be considered;
- Avoid WBS with few activities by subdividing activities to increase WBS size and the number of activities running simultaneously. This subdivision should not compromise the ability to assess the progress of activities, mitigating *analysis paralysis* phenomena by excessive discretization;
- Adopt uniform and short time intervals between TP (between 1 week and 1 month);
- Adopt time intervals between TP that standardizes the relative amount of running activities (in number, PV and duration);
- Privilege the reduction of project duration by *fast tracking*, rather than *crashing*.

The study is supported by 185 observations from 15 independent projects. The models with, and without, robust estimation of standard errors showed similar results. The absence of the group effect, only verified in the SV error, may be related to the sample size. Thus, the robustness of the study can be significantly improved by repeating the analysis adding with more observations of real projects and by adding other variables.

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Appendixes

Appendix A: Description of the characteristics of time and cost planning analyzed (Explanatory Variables)

	ID	Description	Expression
	noTOTAL	Total Number of Project activities, as a measure of the WBS absolute dimension.	
	noTP	Total Number of Project Tracking Periods (TP) as a measure of the absolute number of control points (TP).	
×.	durPROJ	Duration of the Project, as a measure of the duration of the project.	
Primary Variables	durTOTAL	Total Duration of the Project , not considering parallelism, or <i>lags</i> , between activities, as a measure of the absolute execution time of the activities.	\sum Activ. duration in Project
Γ.	BAC	Budget at Completion, as a measure of the absolute PV of the project.	
Prima	noAE	Absolute Amount of Running Activities in TP, as a measure of precedence relationships (parallel activities <i>versus</i> serial activities).	
	costAE	PV of Activities Running in TP (absolute quantity), as a measure of the absolute cost of the activities being carried out.	\sum PV of Activ.running in TP
	durAE	Absolute Duration of Activities Running in TP, as a measure of the absolute duration of the activities being carried out.	\sum Duration of Activ.running in TP
	BAC_noTOTAL	PV (average) by Project activity, as a measure of the influence of the PV of the activities.	BAC Total Activ.of Project
	BAC_noTP	PV (average) by TP, as a measure of the influence of PV controlled in each TP.	BAC Total TP
	BAC_durPROJ	PV (average) per unit of Project Duration, as a measure of PV per unit of project time.	BAC Project duration
riables	BAC_durTOTAL	PV (average) per unit of Total Duration of project activities , as a measure of PV per unit of time of activities.	$\frac{BAC}{\sum Activ. duration in Project}$
Secondary Variables	noAE_noTOTAL	Relative quantity of Activities running in the TP, as a measure of the weighted amount of activities running simultaneously.	Total Activ. running in TP Total Activ. of Project
econd	costAE_BAC	Relative PV of Activities in Execution in the TP, as a measure of the weighted PV of activities running simultaneously.	$\frac{\sum PV \ Activ. \ running \ in \ TP}{BAC}$
60	costAE_noAE	PV (average) per Activity in Execution in the TP, as a measure of the individual PV of the activities in execution.	ΣPV Activ. running in TP Total Activ. running in TP
	durAE_durTOTAL	Relative duration of Activities running in the TP, to assess the weight of the duration of the activities being carried out.	$\frac{\sum Duration \ of \ Activ.running \ in \ TP}{\sum Duration \ of \ Activ. \ in \ Project}$
	durAE_noAE	Duration (average) per Activity running in the TP , as a measure the individual duration of the activities running.	$\frac{\sum Duration of Activ. running in TP}{Total Activ. running in TP}$

Note: durations are measured in x100days and cost in million €

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