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Article

Actuarial Credibility Approach in Adjusting Initial Cost Estimates of Transport Infrastructure Projects

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Abstract: This paper presents a novel methodology based on the modified actuarial credibility approach. It allows for the adjustment of initial cost estimates of public infrastructure projects by accounting for the additional risk/uncertainty factor. Hence, it offers an interesting alternative to other existing forecasting methods. We test our approach by applying data for over 300 major infrastructure projects implemented in Poland between 2004 and 2020. We prove that, despite its simplicity, the actuarial credibility approach can deliver accurate cost estimates compared to more complex methods such as regression analysis (OLS) or machine learning (LASSO). In particular, we show that, although the forecasting accuracy varies among different project categories, actuarial credibility outperforms other forecasting approaches in the majority of cases. As a result, we argue that actuarial credibility should be considered as a relatively simple tool with very modest data requirements that can be easily applied by investors and policy makers in order to improve project planning and avoid cost overruns.

Keywords: actuarial credibility; transport infrastructure investment; cost overruns; risk accounting; regression analysis; LASSO

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1. Introduction

The importance of large transport infrastructure projects is difficult to be overestimated. As claimed in the Global Infrastructure Outlook [1], "the need for infrastructure investment, is forecast to reach USD 94 trillion by 2040, and a further USD 3.5 trillion will be required to meet the United Nations' Sustainable Development Goals for electricity and water". Still, the above estimates can fall short given the consequences of the COVID-19 pandemic and the expected response of the public authorities. For instance, the European Union has recently approved a temporary recovery instrument called NextGenerationEU worth EUR 750 billion. The funding, channeled mainly through the Recovery and Resilience Facility, is supposed to support reforms and investments (including public infrastructure investments) undertaken by the EU Member States. It is likely that similar measures will be implemented in other parts of the world as well, increasing the global value of infrastructure investment in the next years.

Cost overruns are considered as one of the biggest risks related to the major infrastructure investment and transport infrastructure investment in particular. In accordance with the existing literature, in most cases, misinformation about final project costs results from inadequate initial costs estimates (e.g., [2,3]). As a consequence, decisions concerning the implementation of particular investment projects are taken without precise information about the exact costs and benefits. This, in turn, may lead to a misallocation of public funds (e.g., [4–6]).

There exist many studies that focus on the factors behind the risk of cost overruns in transportation investment projects. Still, it is not clear how to properly estimate this risk and how to adjust initial cost estimates in order to counter the possible bias (e.g., [7]).

Traditionally, planners simply used to set additional budget reserve to compensate for potential cost overruns. Yet, in the last two decades, the possibility of accessing historical data on past projects allowed for development of more sophisticated methods. This includes approaches such as reference class forecasting (e.g., [3]), decision-tree analysis [7], regression analysis (e.g., [8]) or artificial neural networks (e.g., [9]). As shown by [10], the above methods differ in accuracy, usability and easiness to understand for decision makers. In most cases, usability and easiness comes at the expense of accuracy. The best example is the reference class forecasting that has been implemented by many governments despite the criticism concerning the precision of its estimates (e.g., [11]). As a result, there is still a need for alternative methodologies that may offer higher accuracy while preserving relative simplicity.

In the present paper we develop a new methodology based on the actuarial credibility (AC) that allows to include risk in initial cost estimates. As compared to other existing methods, our approach provides both high accuracy of estimates and usability. We test our approach applying data for over 300 major infrastructure projects implemented in Poland between 2004 and 2020. We prove that a relatively simple statistical tool may be used instead of more complex approaches (e.g., machine learning) in order to improve project planning.

The remainder of the paper is organised as follows. Section 2 reviews the prior literature on the estimation of initial and actual costs of major transport infrastructure projects. Section 3 discusses actuarial credibility method and its proposed application to the actual project cost estimation. Section 4 provides the results of numerical examples. Finally, Section 5 offers some concluding remarks.

2. Literature Review

Along with the delivery delays, cost overruns are regarded as a main risk related to the successful completion of major transport infrastructure investment projects (e.g., [12]). This is due to the fact that inadequate initial cost estimates may lead to inefficient resource allocation and may cause a social welfare loss (e.g., [13]). Many papers have analyzed the difference between the initial/estimated and actual project costs. In most of cases, the authors have confirmed the existence of significant cost overruns, although, there is no overall agreement concerning their determinants (e.g., [14]). Still, the majority of existing studies confirm that inadequate initial cost estimates are among the main factors behind the existence of cost overruns (e.g., [4]). As a result, many papers provide policy recommendations that underline good forecasting as the key to successful project planning. As claimed by [3], "legislators [. . .] and members of the public who value honest numbers should not trust cost estimates and cost benefit analyses produced by project promoters and their analysts".

According to [15], the cost overruns have been actually given considerable attention by many public agencies. [16] shows that simple mechanisms designed to avoid deliberate bias or unintentional error in cost estimates presented to policy makers were introduced in countries such as Canada, Denmark, Norway, Netherlands, UK and Sweden. Still, as argued by [10], there are a great number of alternative cost estimation methods that can be used in public infrastructure projects. Following [17], the most desirable ones should be at the same time accurate and simple. The problem is, however, that there exists a clear trade-off between accuracy and simplicity of particular estimation approaches. As a consequence, different methods differ in accuracy, usability and understandability to decision makers.

Reference class forecasting (RCF), regression analysis on historical data, machine learning algorithms and unit cost method seem to be the most often applied as cost forecast tools in the existing literature (e.g., [10]). Yet, there can be found a set of other approaches such as decision-tree analysis, Monte-Carlo simulations or structural equation method. In general, there is no consensus on what approach should be considered as the very best. Still, certain methodologies applied by policy planners in different countries have been heavily criticized for inaccuracy in forecasting the initial project costs. This has been, particularly, the case of reference class forecasting—an approach that has become popular among governments worldwide as a tool used to improve the precision of cost estimates. Recently, several studies claimed RCF to be extremely inefficient given that it does not prevent either optimism bias or strategic misrepresentation (e.g., [15,18]). Moreover, the unit cost method cannot be considered as a reliable one, even though it is apparently the simplest and relatively easy to understand one (e.g., [19–21]). Several studies show that, in terms of accuracy, regression analysis is outperformed by machine learning (e.g., [22–25]). However, there is no consensus concerning the best machine learning (ML) algorithm (e.g., [26–29]). On the other hand, there are papers that claim other methods such as structural equation modelling to be more accurate than machine learning (e.g., [9]). Furthermore, while other cost estimation methods may be easy to understand for policy makers (e.g., unit cost method), different ML algorithms can be considered as a particular "black box". Recently, some hybrid approaches were proposed (e.g., [30,31]). Still, it is unclear to what extent the above approaches deal with the accuracy and simplicity trade-off.

The apparent existence of a trade-off between accuracy and simplicity of the existing cost estimation approaches provides an opportunity to develop new methods that combine, as much as possible, accuracy, usability and understandability. Several authors claim that the majority of methods used to calculate initial cost estimates do not include the risk/uncertainty factor (e.g., [4,21]). The forecasting accuracy of the few approaches that account for such risk, is not usually compared to other alternatives (e.g., [11]). This means that there is a clear gap in the existing literature.

This paper fills the above gap by presenting a novel methodology based on the modified actuarial credibility approach. Our approach allows for the adjustment of initial cost estimates of public infrastructure projects by accounting for the additional risk/uncertainty factor. Hence, we provide a relatively simple tool with very modest data requirements that can be easily applied by investors and policy makers in order to improve project planning and avoid cost overruns. The following sections prove that, despite its simplicity, the actuarial credibility approach can deliver accurate cost estimates compared to more complex methods such as regression analysis or neural networks.

3. Methodology and Data

3.1. Methodology

In our analysis we focus on the problems related to accurate forecast of initial project costs. We apply credibility theory in order to verify whether it could be used instead of more complicated and less understandable approaches (e.g., ANN) to adjust initial cost estimates based on traditional cost estimation methods. To the best of our knowledge this is the first time when credibility theory is used in the cost overruns literature.

The actuarial credibility theory is believed to be one of the cornerstones of actuarial science as applied to casualty and property insurance (e.g., [32,33]). Still, the credibility theory is also considered as a new branch of mathematics for studying the behavior of fuzzy phenomena (e.g., [34]). In accordance with [32], the word credibility was originally introduced into actuarial science as a measure of the credence that the actuary believes should be attached to a particular body of experience for rate making purposes. Here, the credibility of the available data has been assessed on the scale which gives 0 credibility to data too small to be any use for rate making and 1 credibility to data which are fully credible. In this sense the credibility theory was initially the branch of insurance mathematics that explored model-based principles for construction of such formulas. However, the development of the theory brought it far beyond the original scope so that today's usage credibility covers linear estimation and prediction in latent variable models more broadly (e.g., [35]). The basic notion of the AC refers to the weight to be given to data relative to the weight to be given to other data. Hence, the basic formula for calculating credibility weighted estimates is given by:

$$\overline{m} = Z \times \hat{m} + (1 - Z) \times \mu \text{ with } 0 \leq Z \leq 1 \tag{1}$$

Z is called the credibility (factor) assigned to the observation that measures the amount of credence attached to the individual experience. At the same time $1 - Z$ is generally referred to as the complement of credibility. Parameter $\hat{m}$ is the observed mean claim amount per unit of risk exposed for the individual contract (actual observation) while μ is the corresponding overall mean in the insurance portfolio (historical observation). Finally, the estimate $\overline{m}$ is also known as a credibility premium. Note, that if the body of observed data is large and not likely to vary much from one period to another, then Z will be closer to one. On the other hand, if the observation consists of limited data, then Z will be closer to zero and more weight will be given to other information (e.g., [36]).

There are two main approaches towards the credibility formulas: a limited fluctuation credibility theory (classical credibility) and greatest accuracy credibility theory (Bühlmann credibility). In more descriptive statistical terms, they could appropriately be called the "fixed effect" and the "random effect" theories of credibility (e.g., [35]). The limited fluctuation credibility follows the approach by [37] and attempts to limit the effect that random fluctuations in the observations will have on the estimates. The greatest accuracy credibility, also referred to as least squares credibility, is based on the theory by [38,39] and aims at the minimization of the square of the error (MSE) between the estimate and the true expected value of the quantity being estimated.

The latter approach shows that the optimal estimator is the conditional mean given by:

$$\check{m}(X) = \mathbb{E}[m|X] \tag{2}$$

where $\check{m}(X)$ is a function of individual data X.

In this case the MSE is described by:

$$\check{\rho} = \mathbb{E}\mathbb{V}ar[m(\Theta)|X] = \mathbb{V}arm - \mathbb{V}ar\check{m} \tag{3}$$

where $m(\Theta)$ is a random variable and Θ is a random element Θ representing the unobservable characteristics of the individual risk.

Note that, in statistical terminology, $\check{m}$ is the Bayes estimator under squared loss and $\check{\rho}$ is the Bayes risk. Hence, not surprisingly, the Bayesian analysis is often used within the actuarial credibility framework in order to produce a better estimate, combining current observations with prior information. Ref. [36] shows also that Bühlmann credibility estimates are the best linear least squares fits to Bayesian estimates (that is why Bühlmann credibility is often referred as Bayesian credibility). In some situations, the resulting formulas of a Bayesian analysis exactly match those of Bühlmann credibility estimation; that is, the Bayesian estimate is a linear weighting of current (actual) information $\hat{m}$ and prior (historical) information μ with weights Z and $(1 - Z)$ where Z is the Bühlmann credibility.

Following Bühlmann (1969), parameter μ and the weight Z can be calculated as:

$$\mu = \mathbb{E}m(\Theta) = \mathbb{E}X_j \tag{4}$$

$$Z = \frac{\lambda n}{\lambda n + \phi} \tag{5}$$

where $\lambda = \mathbb{V}ar[m(\Theta)]$, $\phi = \mathbb{E}s^2(\Theta)$ and n stands for the number of observations.

The greatest accuracy credibility (Bühlmann credibility) has many extensions and generalizations concerning the issues related to the linear estimation and prediction (e.g., [40–42]). This allows for its application outside the actuarial science. As a matter of fact, [35] argues that linear estimation and prediction can be also applied in engineering, control theory or operations research. In this sense, the credibility theory counts as a prominent scientific area with claim to a number of significant discoveries and with a wealth of special models arising from applications in practical insurance.

In the case of our study, the application of AC approach as a cost forecast tool requires certain assumptions and amendments in the credibility formula. First, we should assume that the initial cost estimate for a given project should be considered as an observed (actual) information $\hat{m}$. As a consequence, in accordance with our approach we redefine particular variables from Equation (1) as follows:

$$\hat{m} = initial\ project\ cost\ estimate \tag{6}$$

Second, the parameter μ would refer to the expected cost overrun (based on historical observations) weighted by individual project size. In other words μ can be expressed as:

$$\mu = (1 + mean\ RD) * \ initial\ project\ cost\ estimate \tag{7}$$

where RD (real deviation) is a given by $RD = \frac{(real\ cost - planned\ cost)}{planned\ cost}$.

Finally, we need to amend the credibility estimation. This is due to the fact that following the Equation (5) the credibility factor Z increases with the number of observations even if the accuracy of historical estimates decreases. Hence, instead of applying Equation (5) we calculate the credibility factor Z as a share of projects in our sample that are on budget (projects that experience neither cost overruns nor cost underruns):

$$Z = \frac{number\ of\ projects\ on\ budget}{number\ of\ all\ projects} \tag{8}$$

To sum up, following Equation (1), the proposed methodology consists in adjusting initial cost estimates by a risk factor. The latter is estimated using historical data on accomplished projects that compares the initial cost estimates with real project costs. In this sense, our approach should be considered as fairly simple both to understand and to apply. Furthermore, data requirements are not demanding at all—a database with information on expected and real costs of past projects that belong to a given investment category (e.g., roads) would be sufficient. The main steps required to provide the AC forecast for new construction project are shown on Figure 1 below.

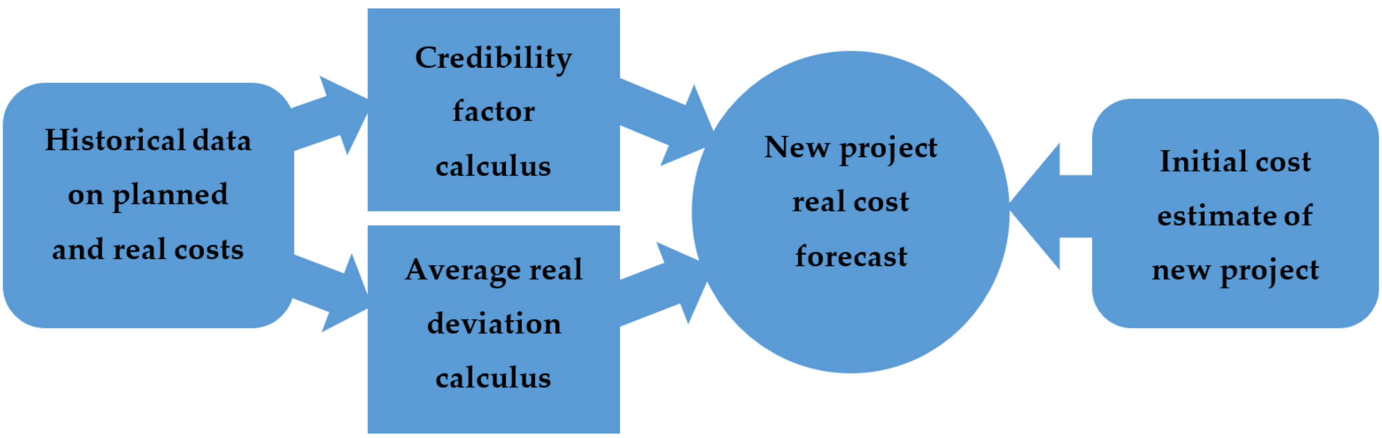

Figure 1. Actuarial credibility flow chart. Source: author's preparation.

3.2. Data

The data used in the present study consists of two different datasets. The first dataset contains 95 road and 50 railway construction projects accomplished in Poland, of which 63 are nationally funded and 91 are co-financed by the EU. The above dataset covers projects with minimum planned and real costs over PLN 90 million that is equivalent to over EUR

20 million. Apart from the planned and real cost of each project, our database provides information on planned and real project elapse, investor type, number of offers during the auctioning process, region of implementation and source of financing (nationally funded or EU co-funded). The presence of several explanatory variables should potentially allow for more precise forecasts based on multiple regression or machine learning algorithms. The projects were accomplished between 2004 and 2020. The main statistics on planned and real costs of the projects can be found in Table 1 below.

Table 1. General statistics concerning planned and real project cost—dataset 1 (in PLN thousand).

	Roads		**Railways**	
Statistics	planned costs	real costs	planned costs	real costs
mean	1,074,104	1,031,646	797,417	638,497
max	6,110,346	5,859,780	5,924,274	5,976,094
min	112,368	91,123	94,575	105,451
observations	95		50	

Source: author's preparation.

Our second database is an extension of the first one. It contains information on 118 road infrastructure projects, 87 railway projects. Additionally, it also includes 76 environmental projects (e.g., wastewater treatment or sewerage) and 96 public service projects (e.g., education, health care or culture). However, this database contains the information on planned and real cost of each project and planned project elapse only. Note that while the second database has more observations in particular investment categories, the number of explanatory variables is reduced. This, however, may be a typical situation for the majority of the project planners. Furthermore, the mean project value is on average lower as compared to the first database. The projects were accomplished between 2004 and 2020. All data come from official sources of Polish government. Detailed summary statistics on planned and real cost of the projects included in the second database can be found in Table 2 below.

Table 2. General statistics concerning planned and real project cost—dataset 2 (in PLN thousand).

	Roads		**Railways**	
Statistics	planned costs	real costs	planned costs	real costs
mean	877,815	842,701	616,661	507,633
max	6,110,346	5,859,780	5,924,274	5,976,094
min	21,944	15,144	22,989	23,194
observations	118		87	
	Environment		Public places	
Statistics	planned costs	real costs	planned costs	real costs
mean	246,985	203,640	80,725	83,328
max	2,213,304	1,813,718	819,000	819,000
min	4664	4626	4807	4342
observations	76		96	

Source: author's preparation.

4. Empirical Results

In order to verify the accuracy of our approach we compare its outcome with forecast based on multiple regression applying ordinary least squares (OLS) and regression-based machine learning algorithm (LASSO). The choice of the alternative methods is based on the literature review. In particular, ref. [10] claim that regression-based analyses and machine learning algorithms are the most frequently used as cost estimation methods. In our case, LASSO applies cross-validation of covariates and prediction is based on selected variables (post-selection coefficients). For ANN, we apply multilayer perceptron (MLP) approach based on backpropagation algorithm with one hidden layer and 5000 iterations. Following other studies (e.g., [23]), we apply a network with one input layer, one output layer and one hidden layer. Comparison of different forecasts is based on statistics such as the mean absolute percentage error (MAPE) and the weighted average percentage error (WAPE).

In the first step, we forecast the expected cost of each project using both the actuarial credibility approach (see example below) and other alternative methods. Our empirical strategy consists in forecasting the expected cost of each project using the data on all remaining projects in our sample. For instance, regarding the road construction projects from the first database, expected cost of project number 1 is forecasted using data for 94 remaining projects. Then, the expected cost of project number 2 is also forecasted using data for 94 remaining projects (including the project number 1). To sum up, the above procedure is repeated n times (where n equals the total number of projects in the database) for each type of project (roads, railways, environment and public services) and methodological approach that we test.

Credibility Calculus Example

Assume that the total number of road projects in the database equals 95. Then, the planned cost of the road construction project number 1 in our database equals 113,197 thousand PLN, the average real deviation (difference between planned and real cost) for all remaining 94 road projects is -0.047 and the number of projects on budget is 23 out of 94. Following the Equation (1), the calculus of expected cost of the above construction project, applying actuarial credibility algorithm, is as follows:

$$expected\ cost = 113,197 * \frac{23}{94} + 113,197 * \left(1 - \frac{23}{94}\right) * (1 - 0.047) = 109,144$$

Note that the expected (forecasted) cost of project 1 is lower than the planned one since the majority of road construction projects in our database experiences are cost underruns rather than cost overruns. In the case of the latter, the expected cost should be greater than the planned one.

In the second step, we calculate the MAPE and the WAPE for the entire sample of 95 road projects, in accordance with the following formulas:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{A_i - F_i}{A_i} \right| \tag{9}$$

$$WAPE = \frac{\sum_{i=1}^{n} |A_i - F_i|}{\sum_{i=1}^{n} |A_i|} \tag{10}$$

where A_i is the real cost (observed) of project i, A_i is the forecasted (expected) cost of project i and n is the total number of projects in the database. Once again, the above procedure is repeated for each alternative methodology and separately for each project subsample (roads, railways, environment and public services). This allows us to compare our methodology with the alternative ones. As noted before, such a direct comparison is rarely found in the existing literature.

Note that the MAPE is an indicator commonly used in the infrastructure forecasting literature. Still, the statistics based on the MAPE give exactly the same weights to all observations in the sample. In our case, however, the value of projects varies significantly. As a result, the MAPE may overestimate the importance of forecast error of particular projects. In such case, overall value of the MAPE may be upward biased. Hence, we also provide error statistics using the WAPE that accounts for the above problem applying weight that measure the size of all projects.

The results of analysis, based on the construction projects from the first database, are presented in Table 3. Given the large number of performed regressions, we cannot provide all summary statistics for particular regressions (detailed forecast results are available upon request from the authors). Hence, we report only the statistics concerning the forecast errors separately for each alternative methodological approach and for each project type (either roads or railways). However, it should be underlined that on average the goodness-of-fit is high. Although only two explanatory variables are statistically significant (planned cost and planned elapse), the R-squared statistics for the OLS regressions are above 0.9 in all of the cases. The better fit is found for roads and worse for railways. Similar fit statistics are observed for LASSO (out-of-sample R-squared above 0.9 for roads and around 0.9 for railways) with cross-validation prediction error below 0.1. It can be observed in Table 3 that, on average, the AC forecast error is lower than the one of alternative approaches, regardless the indicator. In the case of the road construction projects, the comparison of particular forecasting techniques based on the MAPE indicates that AC with an average error around 7% performs better than all other forecast approaches. The second best is LASSO with an average error around 8.4%. The conclusions drawn from analysis of the WAPE are very similar. Again, the AC forecast is performing very well with an average error around 4.3%. It is followed by LASSO with average error around 4.8%. The average forecast error for railway construction projects is much higher as compared to the roads. However, it is not very surprising given that the fit of the OLS regression is worse and that the sample is much smaller—59 observations versus 95 for roads (as claimed in the literature, small sample sizes tend to negatively affect accuracy of machine learning algorithms (e.g., [43])). Still, the AC forecast is outperforming other approaches with the exception of the OLS forecast error measured using the MAPE indicator. In the case of the WAPE, the average error of the AC forecast is around 25.4% followed by OLS with 32.4%. The differences are much smaller in the case of the MAPE—here the average forecast error exceeds 30% for all compared approaches.

Table 3. Performance metrics of different cost forecasting methods—database 1.

Forecasting Method	Roads		Railways	
	MAPE	WAPE	MAPE	WAPE
Actuarial credibility	7.10	4.35	33.09	25.79
OLS	10.15	7.32	31.38	32.38
LASSO	8.37	4.79	33.45	33.56

Source: author's preparation.

Table 4 shows corresponding results for the investment projects from the second database. Mind that, as compared to the first database, the number of observations (projects) is higher. As a result, we have four different categories of projects—apart from roads and railways we also find investment projects related to public services (e.g., education or healthcare) and projects related to environment. The R-squared statistics for the OLS regressions are again above 0.9 in all of the cases. The best fit is found for roads, followed by public services, environmental projects and railways. In the case of LASSO, the out-of-sample R-squared is similar to the OLS R-squared for particular project categories. At the same time cross-validation prediction error is below 0.1 for roads, public services and railways and slightly above 0.1 for environment related projects. On the average, AC again seems to perform well. Still, the MAPE indicator shows the in certain cases other approaches may deliver slightly lower forecasting error. This applies in particular to railway and environment construction projects. On the other hand, as measured by the WAPE, the AC forecast outperforms other approaches for all types of infrastructure investment projects. The forecast error is on the average lower for subsamples with higher number of observations (roads and public service) as compared to the subsamples where the number of available observations is lower (railway and environment).

Table 4. Performance metrics of different cost forecasting methods—database 2.

Forecasting Method	Roads		Railways		Environment		Public Services	
	MAPE	WAPE	MAPE	WAPE	MAPE	WAPE	MAPE	WAPE
Actuarial credibility	8.04	4.45	26.02	23.45	30.17	21.83	13.21	10.82
OLS	9.02	4.81	23.78	26.68	29.65	22.63	13.68	12.92
LASSO	9.02	4.79	23.57	26.39	29.50	22.56	13.68	12.92

Source: author's preparation.

To summarize, we find that forecast accuracy differ significantly between particular methodologies, datasets and investment types. We prove, however, that actuarial credibility approach outperforms other forecasting approaches in the majority of cases, at least, as far as our databases are applied. This implies that the information on planned and real costs of past projects may be indeed sufficient to improve initial estimates of new investments. Our results also suggest that actuarial credibility approach can be effectively used as a tool that allows to adjust initial cost estimates by accounting for the risk/uncertainty factor.

5. Conclusions

This paper presents a novel methodology based on the modified actuarial credibility approach. It allows for the adjustment of initial cost estimates of public infrastructure projects by accounting for the additional risk/uncertainty factor. As a result, we provide a relatively simple tool with very modest data requirements that can be easily applied by investors and policy makers in order to improve project planning and avoid cost overruns. We prove that, despite its simplicity, the actuarial credibility approach can deliver accurate cost estimates compared to more complex methods such as regression analysis or machine learning.

We tested our approach comparing its results with forecasts obtained using alternative methodologies. These are the ordinary least squares (OLS) and the machine learning algorithm such as LASSO. The data used in empirical testing refers to major transport infrastructure projects implemented in Poland between 2004 and 2020. We verified forecasting accuracy of particular approaches by applying two datasets. The first one contains 95 road construction projects and 50 railway construction projects, while the second is comprised of 118 road construction projects, 87 railway construction projects. Additionally it also includes 76 environmental projects and 96 public service construction projects. The main difference between the datasets is the number of explanatory variables.

We found that forecast accuracy differ significantly between particular methodologies, datasets and investment types. For instance, an average forecast error does not reach 10% for the road construction projects, regardless of the database used. At the same time, it exceeds 30% for the railway construction projects in the first database and 20% for projects in the second database. In general, we proved that actuarial credibility approach outperforms other forecasting approaches in the majority of cases. This implies that the information on planned and real costs of past projects may be indeed sufficient to improve initial estimates of new investments. We also showed that the magnitude of an average forecast error depends on the used statistics. Due to the structure of our database, which contains projects with different costs, an average error is higher for MAPE and lower for WAPE. As a result, in our case, WAPE appears to be preferred statistics.

Our results suggest that actuarial credibility approach can be effectively used as a tool that allows to adjust initial cost estimates by accounting for the risk/uncertainty factor. Its simplicity, easiness to understand and very modest data requirements means that it can be considered as a perfect instrument for policy planners. We show that it may outperform other forecast approaches both for transport infrastructure investment projects and other types of infrastructure investment projects. Following our findings, its application could considerably improve the accuracy of cost predictions and thus the effectiveness of public infrastructure investment policies. In particular, it may help to quantify the uncertainties concerning the real financing requirements and thus facilitate the decision- making process. For instance, if we know in advance that the expected cost of transport infrastructure projects is on average 10% higher than the planned one, we might want to clearly define our future investment priorities. Another alternative is to guarantee a budget reserve that equals our expected deviation from the planned costs (e.g., 10%) or to modify the scope of planned projects in order to fit our budget constraints.

Note, that our empirical study relies on the country-specific database. It certainly features certain particularities such as the existence of cost underruns or limited number of statistically significant explanatory variables. In addition, the number of projects that we used in our empirical testing can be considered as relatively low. As a result, one may wonder whether our conclusions would hold for other datasets. In fact, we have contacted several research institutions to get an access to their databases. However, as of yet, we have not succeeded. We fully intend to pursue such additional areas of research. Hence, further empirical evidence is required to fully validate the actuarial credibility approach as a legitimate alternative for existing methodologies. In particular, future research should focus on comparing the forecasting accuracy of the AC approach with machine learning techniques based on advanced optimization algorithms. The number of studies applying the latter to solve different problems related to construction and transportation is constantly increasing (e.g., [26–29]). Still, their superiority over much simpler approaches such as actuarial credibility is yet to be proven.

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