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Simulating the impact of digitalization on retail logistics efficiency

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Purpose: The study uses the results of an efficiency analysis for digitalization within a retail logistics blue-collar work system of professional truck drivers and aims to elaborate an ex-ante efficiency simulation approach for digitalization scenarios.
Methodology: The simulation method combines the efficiency scores of Data Envelopment Analysis (DEA), statistical bootstrapping, and regression analysis. By increasing the original sample size of n=30 truck drivers up to 60,000 samples through 2,000 bootstrap iterations, it is possible to gain a highly significant regression function.
Findings: The mathematical simulation approach can be transferred to alternate scenarios in terms of forecasting efficiency development based on the experience distribution of the workforce.
Originality: As the impact of digitalization on the efficiency of blue-collar work systems is often unknown, this methodology could provide insights for logistics researchers and managers when estimating the efficiency impact of digitalization.

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1 Introduction

Recent advances in the areas of computer science, engineering, robotics, and information science have spawned remarkable digital progress in the fields of production as well as transport and logistics. Focusing on operations management, it can be observed that the ongoing digital transformation is changing the competitive frameworks in which companies are operating in, and consequently their core business operations (Koleva, Andreev, 2018; Lanz, Tuokko, 2017; Lu, et al., 2018; Rajput, Singh, 2019; Zangiacomi, et al., 2017; Roscoe, Cousins, Handfield, 2019). Approaches aimed at enhancing operations have brought high innovation potential to operations management and are often discussed connected to the Industry 4.0 concept (Lasi, et al., 2014; Lee, Bagheri, Kao, 2015; Lee, Kao, Yang, 2014; Stock, Seliger, Seliger G., Kohl H., Mallon J., 2016; Wang, et al., 2016). This describes a set of related technologies and digital solutions in OM that aim to support the development and integration of automation (Stadnicka, Antonelli, 2019; Wollschlaeger, Sauter, Jasperneite, 2017; Pérez, et al., 2019), as well as the exchange of real-time data in production processes (Cao, et al., 2017; Chen, et al., 2016; Zeng, et al., 2019). Thus, most digital innovations in OM concentrate on e.g. digital manufacturing and production management (Borangiu, et al., 2019; Giraldo-Castrillon, Páramo-Bermúdez, Muñoz-Betancur, 2019; Kulkarni, Verma, Mukundan, 2019; Roscoe, Cousins, Handfield, 2019; Wang, et al., 2019), additive manufacturing (Hedenstierna, et al., 2019; Emon, et al., 2019; Hamidi, Aslani, 2019; Jiang, Xu, Stringer, 2019; Kleer, Piller, 2019; Pérez, et al., 2019), or predictive maintenance (Antomarioni, et al., 2019; Chehri, Jeon, Zimmermann A., Chen Y.-W., Howlett R.J., Jain L.C., 2019; Liu, et al., 2019; March, Scudder, 2019). However, most

approaches towards the described digital transformation have the status of conceptual drafts and the effect of the digital transformation is seldom examined with operations research methods or simulation approaches.
Taking up this research gap, an efficiency analysis was developed and applied to evaluate the effect of changing levels of digitalization within the working systems of professional truck drivers (Loske, Klumpp, 2018). However, this method can only explain the verifiable effects of digitalization from the a posteriori perspective, after the digital changeover has taken place. Therefore, an interesting question for scientist and practitioners, as well as the research question of this publication, is: “How could an a priori simulation tool for empirical DEA results be structured, aiming to enable assessments of varying digital transformation scenarios?”.
After this introduction (section 1), the literature review summarizes the technique and results of the efficiency analysis by Loske and Klumpp in 2018, supplemented with further research, including a second efficiency analysis and several regression analyses. Based on these finding, section 4 explains the essentials of a bootstrap approach in nonparametric frontier models (Simar, Wilson, 1998; Simar, Wilson, 2007) applied in the software r and bootstraps the results of one regression analysis presented in the previous section. Furthermore, the effects of bootstrapping are examined from a statistical point of view to test the transferability of the basic data (n=30) on up to 60,000 samples through 2,000 bootstrap iterations. Section 4 closes with the elaboration of the a priori simulation approach. The key findings and further research questions are summarized in section 5.

2 Literature review

This DEA model analyzed the efficiency of truck drivers working in the sector of distribution logistics for a large German food retailing company. The transportation unit is responsible for delivering food and non-food items from the central logistics center to all grocery shops of the relevant delivery area complete and on time as well as for returning recyclable materials plus empty load carriers from the grocery shops back to the logistics center. Focusing the daily business of professional truck drivers and the physical material flows, the work process can be divided in the following steps: (1) Register at the responsible dispatcher in the logistics center, (2) Receive data for delivery tour through mobile device, (3) Load the truck by scanning barcodes on load carriers through mobile device, (4) Receive freight documents from dispatcher, (5) Drive to n grocery shops, (6) Unload cargo at n grocery shops, (7) Return recyclable material and empty load carriers back to logistics center. Aspiring to choose work steps with a maximum of interaction with the digital device, the loading process (2) and (3) were selected for further analysis. Figure 1 presents the applied DEA model.

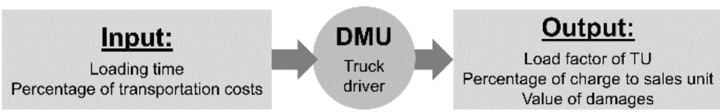


Figure 1: DEA model applied in Loske and Klumpp 2018.

2.1 An empirical analysis for efficiency level in digitalization

A first case analysis (C1) investigated the work system of truck loading for professional truck drivers in retail logistics for 4.5 weeks and aimed to evaluate the efficiency progression of a digital changeover. The analysis contains data of 1,350 delivery tours and focused on a changing level of the digitalized work equipment within retail logistics. Therein, the old mobile devices based on windows mobile software with complex operation principles using a keyboard were replaced by new mobile devices with Android software and a user-friendly full touch display. Another significant modification was the integration of more and new processes into the existing workflow that is handled by the mobile device and has not been included before, e.g., particular application for high-value products like cigarettes, elimination, and digitalization of accompanying documents along with clear menu navigation. The DEA specification constant returns to scale (CRS) is used due to the following reasons: (1) The results of the both models are similar, (2) the analysis does not particularly search for increasing or decreasing returns to scale and (3) it is assumed that the MPSS, the individual performance capability of professional truck drivers, is equal (Banker, Charnes, Cooper, 1984). Figure 2 presents the results of C1.

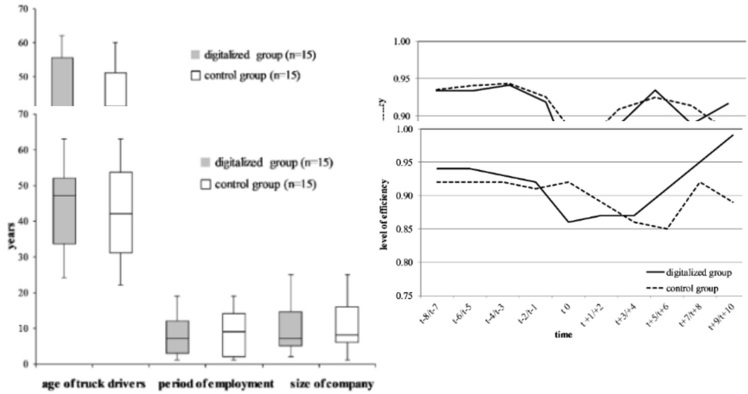


Figure 3: Structure of the study groups and the efficiency curve.

the two examination groups as a longitudinal study, where 4.5 weeks are divided into nine periods with three days each. Through the DEA analysis, it was possible to gain practical knowledge about the development of efficiency when the level of digitalization increased within working systems of retail logistics. Even though the empirical curve progression reflects the theoretical curve progression of Lewin (Lewin, 1947), it was not possible to prove long-term efficiency improvement. Therefore, a second case analysis (C2) was conducted during 9.5 weeks, analyzing data of 2,100 delivery tours. The following figure summarizes the structure of the study groups and the empirical curve progression of C2. Using C2, it was possible to verify the findings of C1 when reflecting the theoretical curve progression presented and furthermore, prove long-term efficiency improvements. Figure 2 presents the results of C2.

2.2 Regression analysis for influencing factors

After elaborating an efficiency analysis for digitalization within blue-collar work systems in retail logistics in the previous chapters, section 3.2. deals with the identification of relevant impact factors for efficiency improvements. Therefore, the data of C2 with the level of efficiency during the digital changeover in t0 is used for nine regression analyses to examine the relationship to exogenous factors integrated into the work system, which are determined as characteristics of the employees: (1) Age (interval scale), (2) Seniority (interval scale), (3) company size (ordinal scale), (4) migration (dichotomous y/n), (5) education (ordinal scale), (6) vocational training (ordinal scale) and (7) job of parents (dichotomous, truck driver y/n). Furthermore, endogenous factors resulting out of the digital changeover, such as (8) satisfaction and (9) motivation (both as interval scale from the questionnaire), are examined. Table 1 summarizes the results of nine regression analyses.

Table 1: Results of regression analysis for influencing factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Obs.	30	30	30	30	30	30	30	30	30
R2	.002	.864	.038	.001	.025	.263	.104	.182	.076

	F Stat.	Re. err.	Adj. R2
(1)	0.030	0.116	-.074
(2)	18.693***	0.043	0.854
(3)	0.514	0.114	- .036
(4)	0.016	0.116	- .076
(5)	0.338	0.115	-.050
(6)	4.643*	0.100	.206
(7)	1.504	0.110	.035
(8)	2.891	0.105	.119
(9)	1.069	0.112	.005

Note: *p**p***p<0.01

The results show that the seniority of truck drivers has a high influence on the level of efficiency during a digital changeover (R2 = 0.864), whereas the other exogenous factors do not influence this scenario. Regarding the endogenous factors, it can be stated that the truck driver's perception of motivation and satisfaction does not affect the truck driver's performance. These findings are used in the next chapter to develop an a priori efficiency simulation for the impact of digitalization. Figure 4 illustrates the regression analysis for seniority (named "TIME") and efficiency (called "EFF").

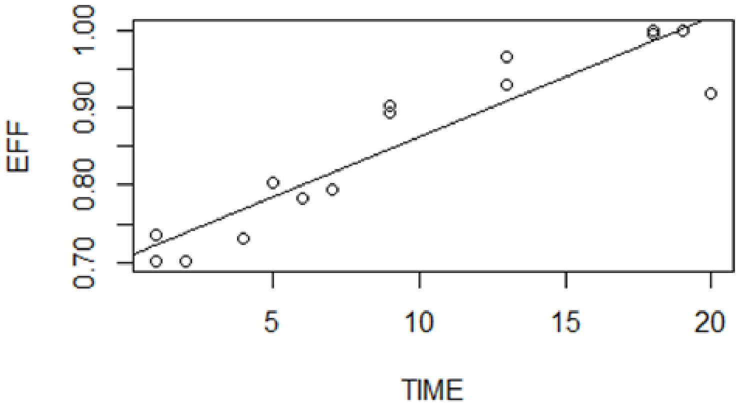


Figure 4: Illustration of regression analysis for seniority and efficiency.

Aiming to ensure that the data is suitable for further investigation, several statistical tests were conducted, including (a) residuals versus fits plot, (b) normal Q-Q, (c) scale location and (d) residuals versus leverage. When conducting a residual analysis, a "residuals versus fits plot" is the most frequently created plot. It is a scatter plot of residuals on the y-axis and fitted values (estimated responses) on the x-axis. The plot is used to detect non-linearity, unequal error variances, and outliers. For (a) it can be determined that the residuals bounce randomly around the 0-line. Therefore, it can be suggested that the assumption of a linear relationship is reasonable. None residual stands out from the basic random pattern of residuals, which indicates that there are no outliers. A Normal Q–Q plot is used to compare the shapes of distributions, providing a graphical view of how properties such as location, scale, and skewness are similar or different in the two distributions. Q–Q plots can be used to compare collections of data or theoretical distributions. Concerning (b), the points form a roughly straight line, indicating a normal distribution. These results are presented in figure 5.

The Scale-Location plot shows whether the residuals are spread equally along with the predictor range, e.g., homoscedastic. On optimum is

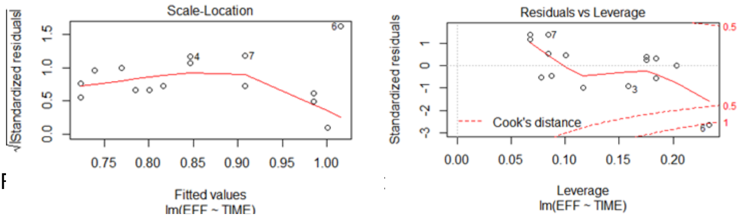
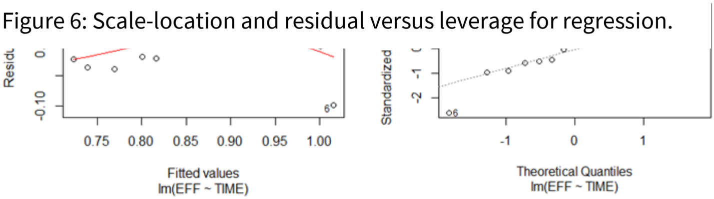


Figure 6: Scale-location and residual versus leverage for regression.



achieved when the line on this plot is horizontal with randomly scattered points on the plot. For (c) this can be observed until an efficiency of 0.95, whereby the data range from 0.96 to 1.00 is not equally spread and DMU6 causes weakness within the regression model. The Residuals versus Leverage plots help to identify critical data points on the model. The points the analysis is searching for are values in the upper right, or lower right corners, which are outside the red dashed Cook's distance line. These are points that would be influential in the model, and re-moving them would likely noticeably alter the regression results. This analysis also indicated that DMU6 causes weakness within the model, also visualized in figure 6.

3 A priori simulation approach

3.1 Basics of statistical bootsrapping

From a statistical point of view, bootstrapping describes a method of testing that relies on random sampling with replacement. The basic idea of the computer-assisted method developed by Efron is to generate n new, wider samples from a given and finite sample. It furthermore allows assigning measures of accuracy in terms of confidence intervals, e.g., α=10%, α=5% or α=1% (Efron, 1979; Efron, 1987; Efron, 1994; Efron, Tibshirani, 2000). The paper entitled "How to Bootstrap in Nonparametric Frontier Models" by Simar and Wilson presents a DEA-applicable approach with up to 1,000 newly generated samples in 1998 and 2007 they introduced a second algorithm which can generate up to 2,000 samples (Simar, Wilson, 1998; Simar, Wilson, 2007). The rDEA package can perform DEA calculations with different assumptions using defined DMUs, input, and output factors and to implement bootstrap calculations with up to 2,000 bootstrap repetitions. The algorithm can be described as follows: dea.robust(X, Y, W=NULL, model, RTS="variable", B=1000, alpha=0.05, bw="bw.ucv", bw_mult=1), whereby:

X a matrix of inputs for observations, for which DEA scores are estimated

Y a matrix of outputs for observations, for which DEA scores are estimated

W a matrix of input prices, only used if model="costmin"

model a string for the type of DEA model to be estimated, "input" for input-oriented, "output" for output-oriented, "costmin" for cost-minimization model

RTS a string for returns-to-scale under which DEA scores are estimated, RTS can be "constant", "variable" or "non-increasing”

B an integer showing the number of bootstrap replications, the default is B=2000

alpha a number in (0,1) for the size of confidence interval for the bias-corrected DEA score

bw a string for the type of bandwidth used as a smoothing parameter in sampling withreflection,"cv"or"bw.ucv" for cross-validation band-width,"silverman"or "bw.nrd0" for Silverman’s (1986) rule

bw_mult bandwidth multiplier, default is 1 that means no change

After running the algorithm with the software r, it provides (1) the DEA efficiency scores for the formulated model, (2) the lower bound, meaning the beginning of the confidence interval of α=10%, α=5% or α=1%, (3) the upper bound, indicating the beginning of the confidence interval of α=10%, α=5% or α=1%, as well as (4) the bias-corrected DEA efficiency scores. The following figure 7 illustrates the results of bootstrap with B=2,000 iterations for C2.

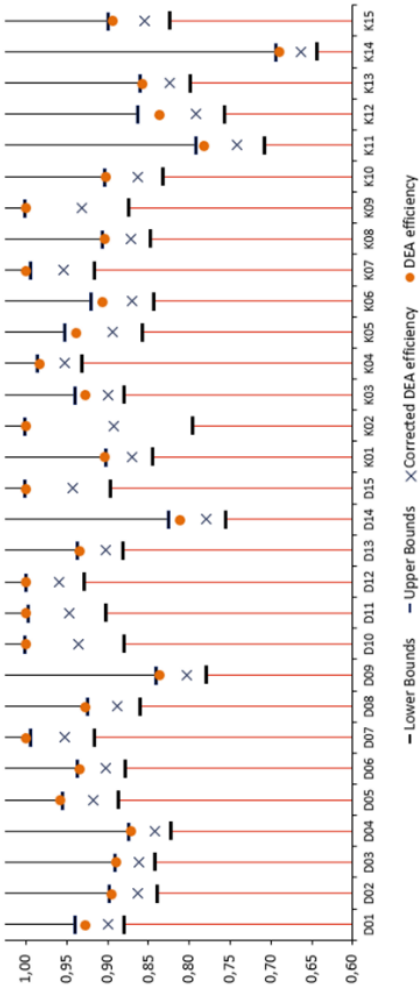


Figure 7: Results of bootsrap with B=1,000 iterations for C2.

3.2 Regression analyses for bootsraps with different iterations

The general idea is to merge the efficiency values of the DEA approach as a dependent variable and the findings of the linear regression analysis, with in-dependent variables, as well as to increase the original sample size nsample for a simulation sample nsim by B bootstrap iterations. As a bootstrap for both variables, the dependent and independent, as well as resampling solely the independent variable, destroys the link of the DMU and its characteristics, bootstrap iterations are conducted on the DEA model and its efficiency values. The efficiency values of period t0 for the digitalization group of case analysis C2 are used with efficiency as the dependent and period of employment as the independent variable. Table 2 opposes the results of 13 regression analyses for 11 bootstraps with the significance levels of $\alpha = 0.05$ and $\alpha = 0.01$. As the number of bootstraps has to be bigger than $1/\alpha$ there is no calculation with less than 50 iterations for $\alpha = 0.05$ and none with less than 100 iterations for $\alpha = 0.01$.

Table 2: Results for 6 bootstrap calculations with α = 0.05 and α = 0.0

	eff.	eff. B=50	eff. B=100	eff. B=200	eff. B=500	eff. B=1000	eff. B=2000
Period employ.	0.015***	0.018***	0.018***	0.018***	0.018***	0.018***	0.018***
	(0.002)	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Const.	0.708***	0.754***	0.753***	0.754***	0.753***	0.754***	0.754***
	(0.020)	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Observ.	30	750	1,500	3,000	7,500	15,000	30,000
R2	0.864	0.812	0.804	0.795	0.788	0.792	0.792
Adj. R2	0.854	0.811	0.804	0.794	0.788	0.792	0.792
Re. err.	0.015***	0.018***	0.018***	0.018***	0.018***	0.018***	0.018***

	eff.	eff. B=100	eff. B=200	eff. B=500	eff. B=1000	eff. B=2000

Period employ.	0.015***	0.018***	0.018***	0.018***	0.018***	0.018***
	(0.002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Const.	0.708***	0.756***	0.755***	0.754***	0.753***	0.753***
	(0.020)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Observ.	30	1,500	3,000	7,500	15,000	30,000
R2	0.864	0.793	0.784	0.789	0.790	0.790
Adj. R2	0.854	0.793	0.784	0.789	0.790	0.790
Re. err.	0.043	0.060	0.062	0.061	0.061	0.061

Note: *p<0.10, **p<0.05, ***p<0.01

The findings show that the values of the regression analysis stabilize between 500 and 2,000 bootstrap iterations for both levels of significance. Furthermore, the $\beta0$ and $\beta1$ values differ marginal between $\alpha = 0.05$ and $\alpha = 0.01$. Due to the higher significance, the linear regression equation $y = 0.753 + 0.0181x$ of $\alpha = 0.01$, which can explain 79% of the regression model's variance, is used for further calculations. To illustrate the effect of bootstrapping calculation on the linear regression model, figure 8 illustrates the linear regression model for 2,000 bootstraps and the development of R2 for increasing iterations with α = 0.05 and α = 0.01.

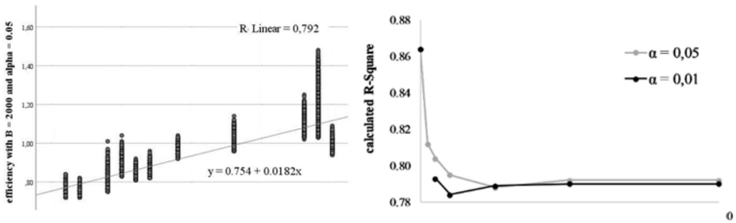


Figure 8: Linear regression model and R2 for increasing iterations.

3.3 Effects of bootstrapping from statistical point of view

Aspiring to shed light on how the statistical bootstrapping and increasing iterations improve the linear regression equation, the developments of the regression analyses are opposed with B=0, B=100, B=200, B=500, B=1,000 and B=2,000 iterations. The residuals versus fitted, the normal Q-Q, the scale location, and the residuals versus leverage are compared by presenting the basic model, as well as the bootstrap models with B=100, B=500, and B=2,000 iterations. The results are visualized in figure 9.

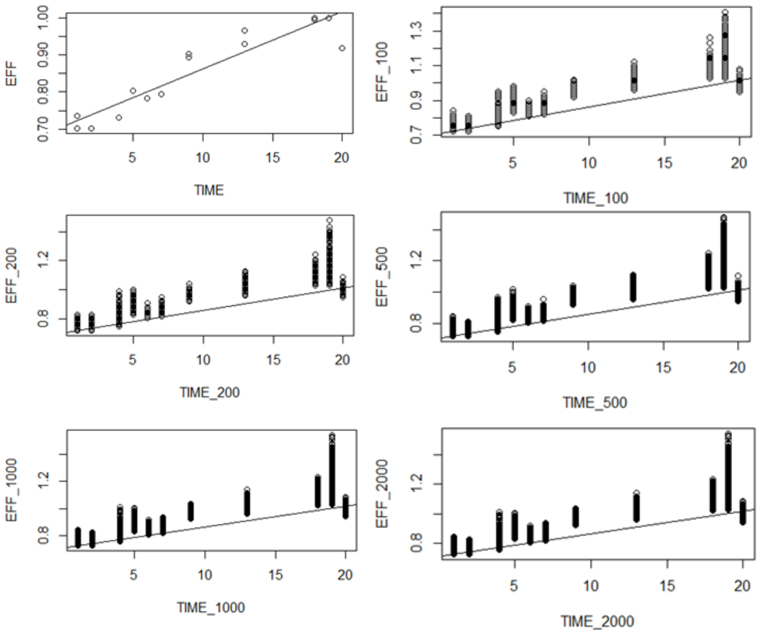


Figure 9: Development of regression analyses.

The regression lines are developing significantly from the basic model to 500 bootstraps, which can also be seen in the R2 values that have been elaborated in the previous chapter. In contrast, the doubling of bootstraps from 1,000 to 2,000 iterations has hardly any notable effect. A further reflection of the bootstrapping results shows that DMUs with an efficiency score of more than 0.90 in the basic model rise into super-efficiency when bootstrapping the results. These DMUs are illustratively separated from the remaining DMUs by a red line. The maximum of 1.40 is already reached with a minimum of B=100 bootstraps, whereas additional bootstraps lower the

maximum efficiency on 1.35. Super-efficiency implies the possible capability of a DMU in increasing its inputs and reducing its outputs without becoming inefficient (Chen, Du, Huo, 2013). In the DEA literature, approached focusing super-efficiency examine, e.g. identifying outliers, ranking the extreme efficient DMUs or calculating efficiency stability region. The results are visualized in figure 10.
Examining the development of residuals versus fitted, it can be stated that

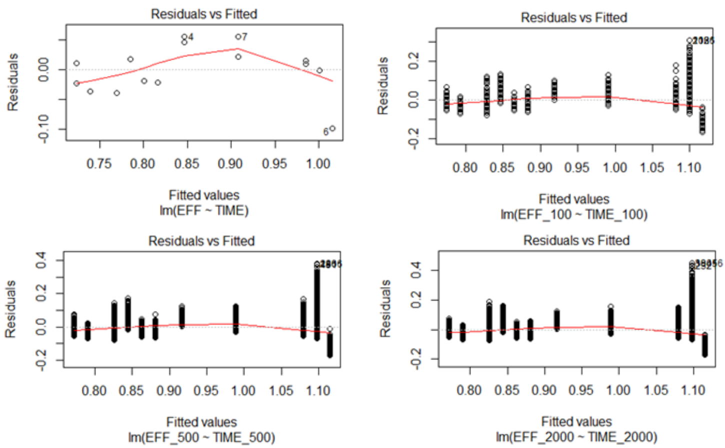


Figure 10: Development of residuals versus fitted.

the residuals approximate around the 0-line when increasing the number of observations by statistical bootstrapping. This underlines the assumption that a line-are relationship is reasonable, which improves with increasing iterations.

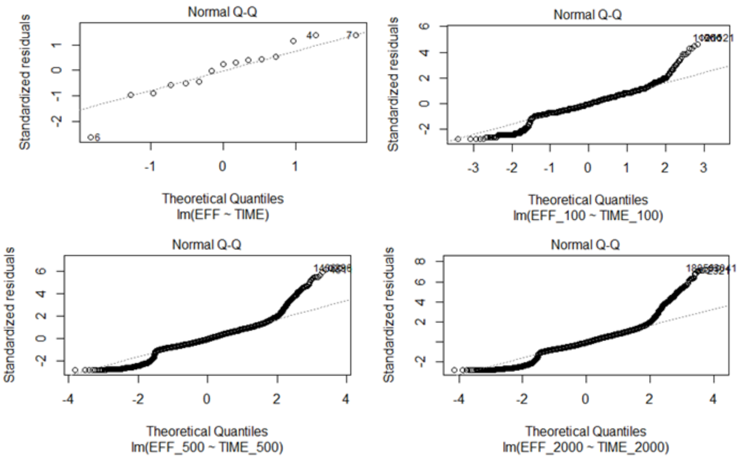


Figure 11: Development of normal Q-Q.

For the basic population, the points form a roughly straight line, indicating a normal distribution. When increasing the samples via bootstrapping the super-efficient DMUs leave this line significantly.

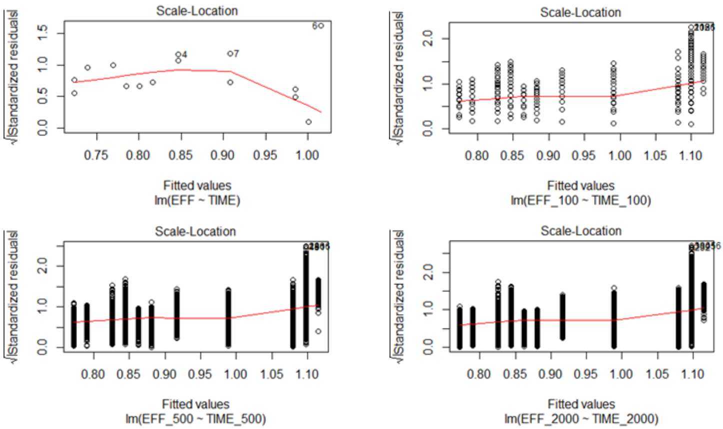


Figure 12: Development of scale location.

The aspired optimum of the scale location, which is a horizontal red line indicating a constant scale-location with randomly spread points on the plot, is reached when increasing the bootstrap iterations. Thereby it seems irrelevant if 100 or 2,000 bootstrap iterations are conducted.

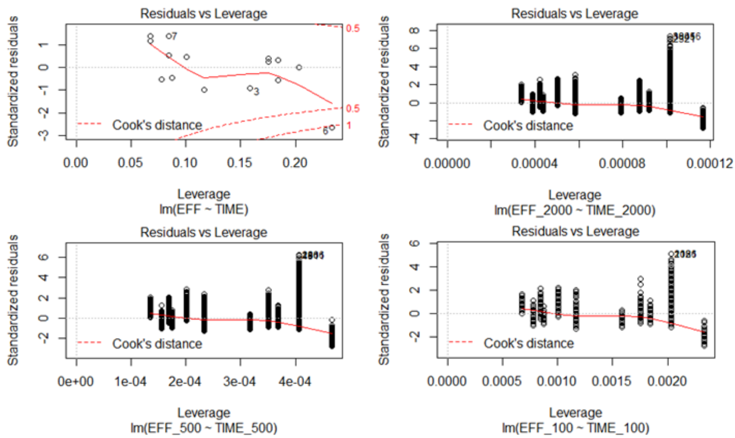


Figure 13: Development of residuals versus leverage.

The influence of the data point DMU6, which has been identified by examining the Cook's distance line in the basic model, can significantly be lowered when bootstrapping the empirical DEA results. While the increase of bootstraps from 100 to 500 results in an approximation of all data points to the 0-line, further extensions seem not to influence the results. The deviation of data points in the right area of the graphs results from the super-efficient DMUs.

3.4 An a priori simulation approach

With a stable and highly significant linear regression equation, it is now possible to accelerate (1) a managerial approach by focusing on a temporal and an inductive simulation when answering current issues of retail logistic managers e.g. "How is the efficiency level of truck drivers for digital changeovers within our retail logistics sector in 10 years?" or "How will the efficiency curve develop during a digital changeover in another depot" and (2) a methodological approach answering questions e.g. "How can the efficiency level for digital changeovers, concerning all truck drivers in a certain country, be evaluated?".

For a first managerial approach, the verified linear regression equation efficiency = 0.753 + 0.0181 × seniority is applied to determine the total efficiency of the retailer's depot by an inductive simulating of the basic population with all 173 truck drivers. Whereby the sample (min.= 1; max.= 20; mean= 9.66; sd = 6.758) had an average efficiency of 0.86, the basic population (min.= 1; max.= 27; mean= 9.62, sd = 5.62) shows an average efficiency of 0.88. By applying the same logic to another depot of the retailer, it was possible to simulate the efficiency during a digital changeover for further

123 truck drivers (min. = 1; max. = 38; mean = 10.55, sd = 7.504) with an average efficiency of 0.87. Besides the presentation of the results, it has to be mentioned that it is crucial to apply the linear regression equation to every single DMU. Simply entering the mean value of the depot into a formula disregards the underlying standard deviation which spans the wrong value for the average efficiency. Figure 14 illustrates the histograms of depots used for inductive simulation that were the basis for our analysis.

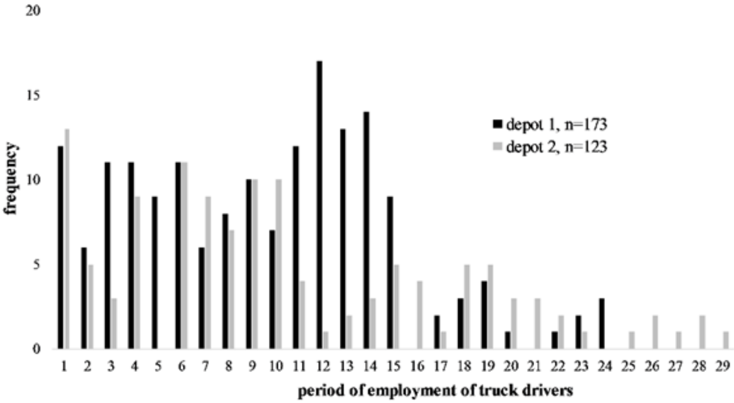


Figure 14: Histograms of depots used for inductive simulation.

A second managerial approach aims to elaborate a temporal simulation that is tested under the following assumptions: (1) The number of DMUs stays constant with n=30, (2) The developed regression model for the digital changeover can be transferred on digital transitions happening in the future and (3) Retiring truck drivers are replaced by drivers with age occurring in the sample. For the simulation, the data of case analysis two is used, and the age of the truck drivers is raised by ten years, causing retirements that are presumed with 60 years of age and marked grey. The age and the period of employment for the new drivers are selected randomly by choosing with repetition out of the occurring ages from the sample set. Table 3 summarizes the results of the temporal simulation.

Table 3: Results of the managerial approach for temporal simulation.

Sample Øeff. = 0.855				Simulation Øeff. =0.916			
DMU	empl.	age	eff.	DMU	empl.	age	eff.
DMU1	4	54	0.73	DMU1	9	38	0.89
DMU2	9	35	0.89	DMU2	19	45	1.00
DMU3	2	53	0.70	DMU3	1	24	0.74
DMU4	9	50	0.90	DMU4	13	47	0.93
DMU5	13	63	0.93	DMU5	5	29	0.84
DMU6	20	28	0.92	DMU6	30	38	1.00
DMU7	13	29	0.96	DMU7	23	39	1.00
DMU8	1	24	0.70	DMU8	11	34	0.95
DMU9	7	47	0.79	DMU9	17	57	1.00
DMU10	18	47	1.00	DMU10	28	57	1.00
DMU11	19	32	1.00	DMU11	29	42	1.00
DMU12	18	51	0.99	DMU12	2	50	0.70
DMU13	6	38	0.78	DMU13	16	48	1.00
DMU14	5	61	0.80	DMU14	1	24	0.74
DMU15	1	37	0.74	DMU15	11	47	0.95

On this basis, the simulation calculates the efficiency values for all DMUs where the period of employment does not occur in the sample (DMU6,

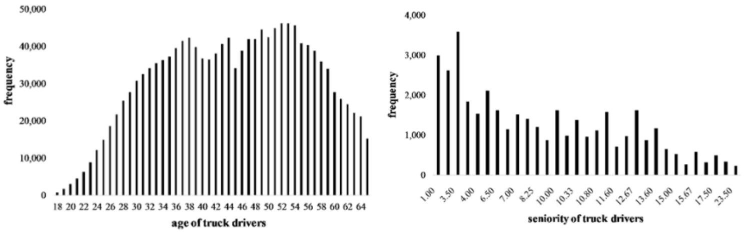


Figure 15: Histograms for the distribution of parent population.

DMU7, DMU8, DMU9, DMU10, DMU11) by using the linear regression function. The temporal simulation predicts an average level of efficiency of 0.916 for a digital changeover within the examined retailer's depot in 10 years (t0=0.855). To address a methodological advancement, the connection between efficiency and period of employment, expressed by efficiency = 0.753 + 0.0181 × time of employment, is applied to a parent population. Therefore, the dataset "GB Driving Licence Data" issued by the Driver and Vehicle Licensing Agency (DVLA) of Great Britain (GB) containing information about age and type of license for 1,512,167 license holders was used. Relevant data was selected by choosing the truck driver license categories C and CE, licenses and exclude pre-driving test learner licenses. To generate a dataset for the seniority of truck drivers, the average seniority per age extracted from the retailer's depots dataset, which was used previously, is applied. The total efficiency of 0.89 is then calculated by applying the linear regression line in the distribution of seniority and weighting them with the total number of driving licenses per period of employment.

Figure 16 summarizes the a priori simulation approach by illustrating the framework of requirement taken from (Loske, Klumpp, 2018), the method

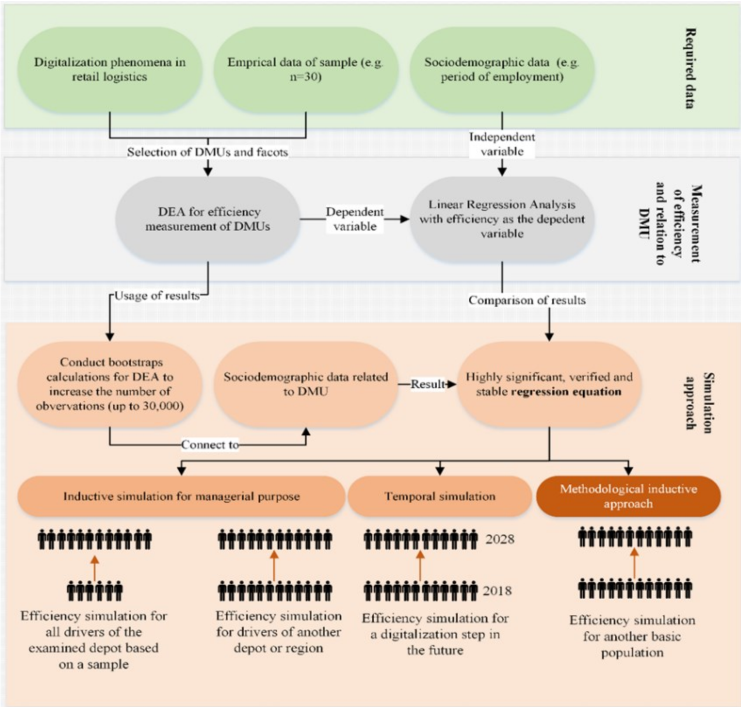


Figure 16: Requirements and outcomes for the simulation.

for measuring the relative efficiency by applying DEA as well as the combination of empirical efficiency values, bootstrapping and regression analysis. The a priori simulation approach can have the character of (1) an inductive simulation for managerial purpose, (2) a temporal simulation and (3) a methodological inductive approach.

4 Conclusion

Based on the efficiency scores of retail truck drivers, a regression analysis stated a strong statistical linear impact of seniority on the efficiency during digital changeovers, which was used to develop an inductive simulation approach. The combination of DEA, statistical bootstrapping, and regression analysis enabled the development of a significant regression function for the relationship of seniority and efficiency due to 60,000 simulation samples. Concerning the ongoing digital transformation, this inductive simulation approach can potentially be adapted to gain anticipative insights regarding the digitalization phenomenon for scientists and logistics managers. Future research would have to address among others the following points: (1) A possible simulation approach based on nonlinear regression, (2) A further simulation approach based on nonlinear regression with multiple variables and (3) A simulation approach for alternative digitalization scenarios in logistics, e.g. order picking or cargo handling.

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