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CHANGES IN TRANSPORT BEHAVIOUR OF THE CZECH POPULATION CAUSED BY STATE OF EMERGENCY

Summary. This article presents the results of an extensive questionnaire survey focused on changes in the transport behaviour of the population of the Czech Republic immediately after the government's announcement about the measures implemented to prevent the spread of COVID-19. The questionnaire aimed to determine the changes in the use of the mode of transport for regular travel to work, school, or for shopping, as well as to determine the changes in the frequency of these travels according to monitored socio-demographic groups of inhabitants and specified size groups of settlements. This article contains a statistical evaluation of these changes in the transport behaviour of the population using sophisticated statistical tools. A method is proposed for estimating the number of passengers in public transport using a linear regression model based on the data from conducted transport behaviour survey. In this paper, the Data envelopment analysis (hereinafter referred to as DEA method) within the case study in the South Bohemian Region is also used to determine whether the COVID-19 measures have reduced the efficiency of public transport.

1. INTRODUCTION

A state of emergency was declared and government measures were adopted in the Czech Republic (hereinafter referred to as CR) in order to prevent the spread of COVID-19 (generally referred to as the lockdown). The global pandemic of this disease has undoubtedly immensely affected the everyday activities of citizens, their psychological health, their activities, as well as their physical health. This societal deviation from the everyday life of the population is reflected in many areas of life, including the transport behaviour of citizens.

Researchers from many countries have investigated how the patterns of transport behaviour have changed due to the lockdown. Governments in different countries have different approaches to mitigating the socio-economic impacts of the pandemic; lockdowns have been of different natures and lengths in different countries. Some of the first authors to come up with the results of their research were researchers from the University of Wien, who conducted their research in several European countries. One of their key findings is a significantly lower willingness to travel, especially using public transport (hereinafter referred to as PT) [1].

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Awad-Núñez et al. [2] carried out an extensive survey in Spain in order to find how the patterns of transport behaviour changed in different groups of citizens and the extent to which these groups of citizens were willing to pay more for PT services [2]. Their results are of great importance, especially for carriers, who can implement various measures concerning means of transport in order to retain their customers. A similar view was shared by many other researchers [3-5] (e.g. in Poland, a survey concerning the users of PT in Gdańsk was performed) [6].

Examining the impact of the COVID-19 pandemic on citizen behaviour in the area of mobility requires an interdisciplinary, multidimensional, and holistic approach [6-10]. Further studies and surveys are needed, especially from the psychological point of view, to ensure further development of sustainable mobility, which would facilitate an understanding of the increased levels of stress, aggression, worries, or anxiety arising from societal changes that may affect transport behaviour [11]. In the Czech Republic, private motor vehicle transport is still a dominant mode of transport; although its share on the overall modal split has been significantly reduced in relation to the introduction of teleworking (a kind of remote work), the number of private road vehicle users still seems to be increasing compared to the number of PT users [12]. However, many citizens used the lockdown as an opportunity to utilise active means of transport (e.g. cycling, walking) in towns. Towns and governments at different levels should focus on maintaining the reduced share of private motor vehicle transport on the overall modal split even in the post-COVID-19 period, when it will probably be much more difficult for PT to retain its customers [13].

The authors of the present article carried out a questionnaire survey among the population of the Czech Republic in order to determine the extent to which selected patterns of citizen transport behaviour changed in the state of emergency declared by the government of the CR in relation to preventing the spread of COVID-19.

2. DATA AND METHODOLOGY

The selected method for obtaining the required information on citizen transport behaviour was an online questionnaire. A questionnaire entitled "The influence of measures against the spread of COVID-19 on the transport behaviour of the citizens of the CR" was created using an online portal for creating questionnaires and surveys. The data was collected between 1 June 2020 and 5 July 2020; the questionnaire was distributed to respondents (mostly through public discussion groups of citizens of various Czech towns) via online social networks. During the first wave of the pandemic, the state of emergency in the Czech Republic was declared from 12 March to 17 May 2020. Thus, the data was collected after the state of emergency had been cancelled – specifically, during the period when the government measures were released – and the respondents commented on the state of emergency retrospectively. The questionnaire was structured so that, in the first part, the respondents provided information about their socio-demographic characteristics. The next set of questions concerned the participants' form of employment or study. For these groups of citizens, the modes of transport used for commuting to work or educational institutions – before the state of emergency had been declared and during the state of emergency – were monitored. Other questions in this category concerned the frequency of journeys to work or school before the declaration of the state of emergency, as well as the usual travel time or other significant measures of transport behaviour.

Another set of questions concerned the shopping habits of citizens in terms of their transport behaviour. The main objective was to determine modal split prior to and during the state of emergency, closure of shopping centres, as well as changes in working hours.

In total, responses from 3,148 respondents were obtained through the questionnaire survey. Based on the postal codes of the addresses given by the respondents in the first part of the questionnaire, individual municipalities were divided into size categories by the authors. The postal codes indicated in the questionnaire were compared with the database of Czech Post (relevant municipality), and the authors looked up the number of inhabitants in specific municipalities in the database of the Czech Statistical Office.

Based on the above, the postal codes (municipalities) were divided into three size categories:

1. Towns with 100,001 inhabitants or more – 560 respondents;
2. Towns with 10,001-100 000 inhabitants – 1,815 respondents;
3. Towns and municipalities with 10,000 inhabitants or fewer (rural areas) – 772 respondents.

When categorising the postal codes, the authors also considered the factor of municipality catchment area by including the municipalities within a certain distance from the municipality in a certain subordinate group in the same subordinate category (included in the agglomeration of a larger municipality).The distribution of the number of respondents in individual size categories corresponded to the actual distribution of inhabitants in the structure of municipalities in the CR to a certain extent. Based on the obtained data, the authors also proposed a method for estimating the number of passengers, which can be applied to similar emergency situations and, thus, used to predict changes in population transport behaviour for a specific case study. Specifically, the calculation estimation is determined using a linear regression model.

Another part of the paper utilises the DEA method to determine whether the COVID-19 pandemic has reduced the efficiency of PT in the South Bohemian Region. The years 2018-2020 were chosen as the production units whose efficiency will be compared. Inputs and outputs related to PT in the South Bohemian Region for the given period were determined for all years.

3. RESULTS

The following results should be considered the most fundamental outputs of the evaluated questionnaire survey. Due to the extent of the questionnaire, it is not possible to present all information obtained in this article. The respondents are divided into different age groups, with the 30-39 age group showing the highest representation (862 respondents). The other age groups included 814 respondents aged 19-29, 705 respondents aged 40-49, 411 respondents aged 50-59, 232 respondents aged 60-69, 59 respondents aged 70 and older, and 53 respondents aged 18 or younger.

As for the questions concerning livelihood and social status, 266 respondents were students or pupils, while 116 respondents were employees in primary employment and studying. Another 1,645 respondents were employees in primary employment, and 197 respondents were self-employed. These groups of respondents were taken as determinative for the analysis of citizen transport behaviour in terms of commuting to work and educational institutions.

Another group of respondents was not considered for the purposes of the aforementioned analysis but was included in the analysis of shopping trips and travelling to take children to kindergartens and other educational facilities. Specifically, 438 respondents – homemakers (mostly on maternity leave), 86 unemployed respondents, 44 people without any taxable income, and 269 respondents who claimed to be retired – comprised this group. The majority of respondents who chose the “other” option (86) wrote “invalidity pension”. In the section concerning pupils and students, the answers showed that in the vast majority of cases, participants’ school facilities were closed due to government regulations (88% out of 266 respondents), and, thus, they did not travel regularly.

In the case of the economically active population, 1,876 respondents (40%) did not notice any change in the areas of work and commuting to work, while 26% of the respondents changed their working hours. Furthermore, 14% of the respondents stated that their workplace was closed due to the state of emergency, and 13% of the respondents stated that they worked from home instead of commuting to work. Moreover, 5% of the respondents also claimed that they did not go to work because they had to care for a family member. Due to the extent of the initial data, no data is not presented in this section of the article; in the following chapters, the authors focus only on the basic factors that led to the change in citizens’ transport behaviour.

3.1. Changes in frequency of commuting to work

One section of the questionnaire deals with identifying the frequency and number of journeys participants made to work before and during the state of emergency. The graph in Figure 1 shows the changes during the state of emergency – specifically, the responses provided by the respondents were divided into groups according to the size of the towns and municipalities where they live. The relative distribution shows that the structure of changes in the number of journeys was approximately the same throughout the Czech Republic; the only difference was that more citizens were allowed to work from home in big towns.

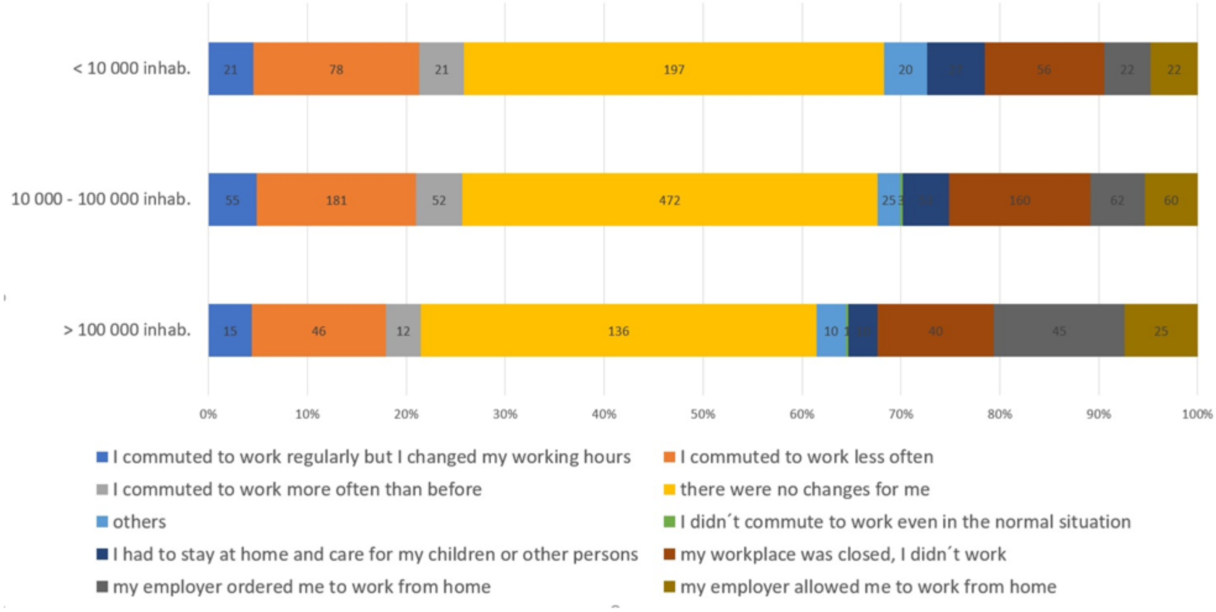

Fig. 1. Changes in commuting to work according to respondents' addresses

A comparison of the individual workplaces shows a significant change resulting from the closure of shops and other workplaces regularly open to the public, which had to be closed per the state of emergency. This, however, includes shops that had to remain open (e.g. grocery stores, drugstores). A similar situation was observed in the education sector, as all educational institutions were closed, and most employees worked from home. Significant changes were also noticed in the sectors of manufacturing, warehousing, and logistics, where workplaces were closed and shifts were changed, among other differences. This had a significant impact on commuting to work.

During the preparation of the questionnaire, a hypothesis was formulated that there was no change in the frequency of journeys to work or school for 50% of the respondents. The hypothesis was rejected based on the results of the chi-square goodness of fit test ($p<0.001$). It was confirmed that there was a change in the frequency of journeys to work for more than 50% of respondents, as 1000 respondents out of 1855 stated that they had experienced such a change.

3.2. Changes in the mode of transport used for commuting to work

During the state of emergency, 1,283 economically active persons continued commuting to work (regularly five days a week or with a different frequency – see the basic evaluation in the previous part). The responses were further analysed from different perspectives, one of which was a change in the selected mode of transport. One of the questions asked whether respondents experienced a permanent change in their selected modes of transport for commuting to work directly due to the state of emergency. Out of 1,238 respondents, 149 answered positively. In particular, respondents declared a shift from PT to passenger cars (either as a driver or a passenger). In response to the additional question related to the reasons for changing the means of transport, the vast majority of the respondents (91%) mentioned a fear of becoming infected; other reasons included the change in working hours and the flexibility and comfort of using a car.

Compared to smaller municipalities (rural areas), larger towns presented a higher percentage of respondents who chose different modes of transport for commuting to work after the state of emergency was declared. This difference corresponds to the higher share of PT users in larger towns before the state of emergency. In towns with more than 100,000 inhabitants, the relative share of the change in selected means of transport was 19%. The change in citizen transport behaviour in the three mutually compared subgroups was statistically significant ($\chi2 = 15.3$, $df = 2$, $p < 0.001$).

The positive answers to the question concerning the change in the modal split show the specific change (i.e., which mode of transport was used after the change). Most respondents (77%) stated that they had stopped using PT. Furthermore, 73% of the respondents who stopped using PT for commuting to work decided to use passenger cars for commuting. A test of marginal homogeneity was run to identify the five most commonly used modes of transport before and during the state of emergency, both in the whole dataset and in the subset according to the size of municipalities where the respondents live. A statistically significant difference was confirmed for all cases.

The most frequently used modes of transport were compared using the McNemar test (or the exact binomial distribution test) with a modified significance level due to multiple comparisons (Bonferroni correction). Fig. 2 shows the total shares in the representation of the individual modes of transport on all journeys to work within the statistical dataset.

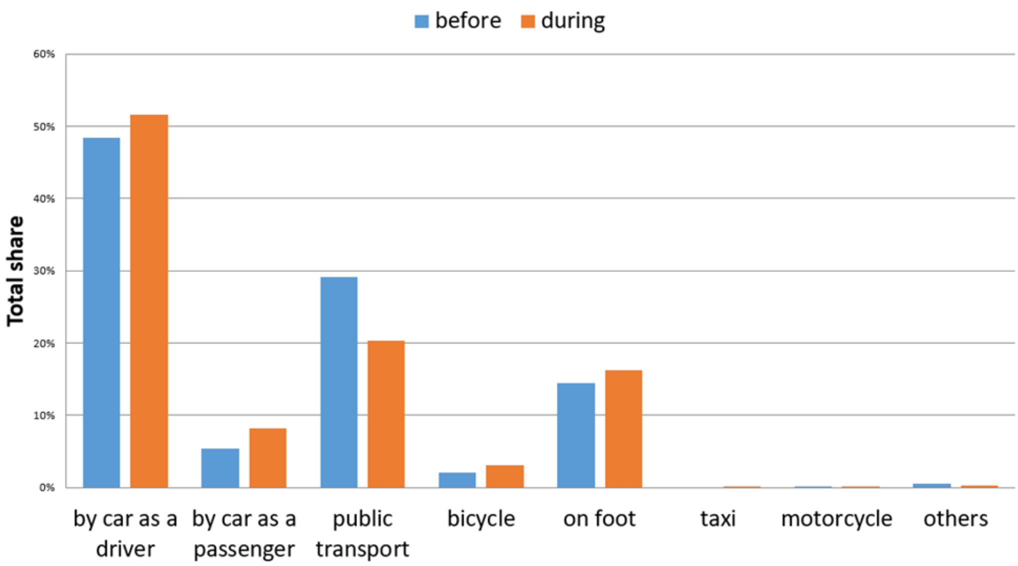

Fig. 2. Share of individual modes of transport on journeys to work within the dataset

The significance levels (p) are lower than 0.05, indicating statistically significant differences in the representation of the five compared categories before and during the state of emergency (by car as a driver, by car as a passenger, by PT, by bicycle, and on foot). Individual means of transport were compared for individual size categories of municipalities. When analysing the changes in used modes of transport for commuting to work in individual size categories of municipalities, the McNemar test identified a statistically significant difference in the representation of these categories of modes of transport used before and during the state of emergency (Tab. 1).

Fig. 3 below shows a Sankey diagram that graphically represents the change in means of transport used in relation to other effects of the state of emergency as indicated by the answers provided by the respondents (e.g. workplaces closed, schools closed, working from home, taking care of a family member). The diagram also indicates cases where no journeys to work or schools were made during the whole period of the state of emergency. Thus, it is only during the period of the state of emergency and the loosening of government restrictions in which people frequently stayed at home.

The results indicate that many respondents did not regularly commute to work or school for the reasons specified above (closure of workplace or schools, caring for a family member, working from home). In total, this situation applied to 853 respondents out of 2,138 (approx. 40%). Many respondents who continued working from home used a passenger car for travelling.

Table 1

Significant changes in means of transport used for commuting to work

Category of municipalities	Increase	Decrease
Over 100,000 inhabitants (n = 201)	By car as a passenger On foot	PT
10–100,000 inhabitants (n = 728)	By car as a driver By car as a passenger bicycle On foot	PT
Under 10,000 inhabitants (n = 299)	By car as a driver	PT

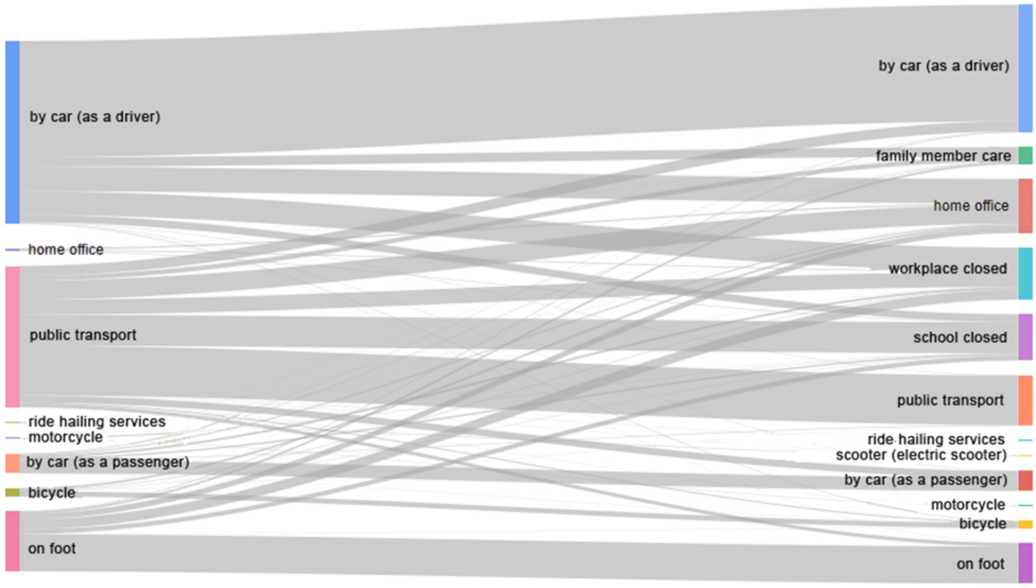

Fig. 3. Sankey diagram of changes in using modes of transport in the case of employed people and students during the state of emergency in CR

3.3. Changes in citizen shopping habits in relation to transport

The questions included in the section concerning shopping habits were compiled such that it was possible to gain awareness of the nature of citizen shopping habits and the means of transport used (or the frequency of journeys to shops). A total of 3,148 responses were obtained.

An interesting finding regarding the number of journeys made before the declared state of emergency is that more than 50% of journeys were made for shopping as an individual journey, while 44% of the respondents stated they shopped on the way to/from work or school. Of the total number of individual journeys, a passenger car was used in 73% of cases (with respondents either being the driver or a passenger) – thus, these are the journeys considered as journeys with the use of private motor vehicle transport (PMVT) in addition to journeys to work made by car.

As for the changes in citizen shopping habits during the state of emergency, 27% of the respondents claimed that they did their shopping and, thus, travelled as often as before the state of emergency (i.e. there was no change). In 51% of cases, the respondents stated they preferred to buy larger volumes of goods within one journey and go shopping less often. In 10% of the cases, the respondents claimed that they had started to buy food online for the first time due to the state of emergency or that they bought food and consumer goods online more often than before. Also, 4% of the respondents stated that someone else did their shopping for them for reasons connected with the state of emergency.

Another section of questions concerned the mode of transport the respondents used for travelling to go shopping. After filtering the answers, 2,995 responses were obtained from the respondents to the question of which means of transport they had (usually) used before the state of emergency and during the state of emergency and the related crisis.

In general, there was an increase in the number of journeys for which the respondents in the state of emergency used a passenger car more than before. A significant change can be seen in the case of PT, as the majority of passengers stopped using PT to walk. This is largely indicated in the responses to the questions concerning the nature of shopping – in these cases, people preferred shopping in smaller shops close to their homes that were accessible by walking. A similar number of PT users preferred to use passenger cars for shopping during the state of emergency.

Within the three monitored size categories, it was found that citizen transport behaviour did not differ depending on the size of their municipality. The differences in citizen transport behaviour in individual groups are statistically insignificant ($\chi 2 = 5.28$, df = 2, $p < 0.071$).

For towns with populations under 100,000, there was a higher share of inhabitants who used passenger cars for shopping trips (67%). In smaller municipalities with a number of inhabitants not exceeding 10,000, such a change was observed in 76% of cases. In towns with more than 100,000 inhabitants, the difference in using modes of transport for shopping was not significant, as passenger cars were used in 50% of cases, while pedestrian traffic also represented a significant share (36%).

Fig. 4 shows total shares of the representation of the individual modes of transport for all journeys made for shopping. The representation includes respondents who responded “online shopping with home delivery” and the respondents to whom food was regularly delivered by another person (both are included under the category “delivery”). For these respondents, the form of shopping did not change during the state of emergency.

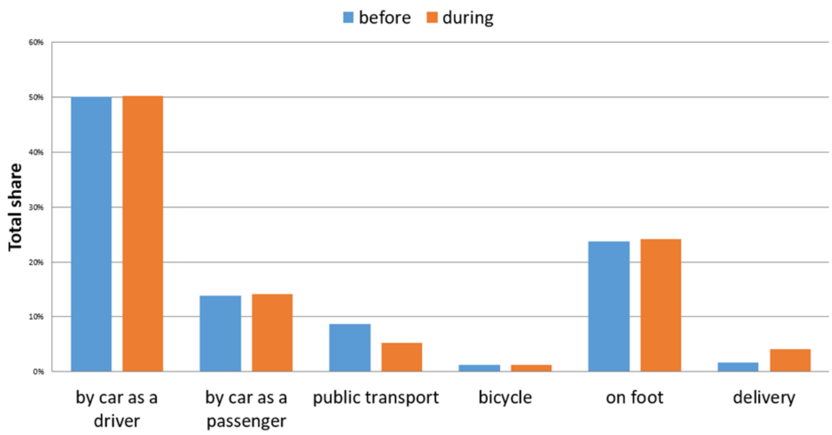

Fig. 4. Absolute number of means of transport used for shopping during the state of emergency in comparison with means of transport used before the state of emergency

Comparisons within the individual most used modes of transport were carried out using the McNemar test (or exact binomial distribution test) with a modified significance level since multiple comparisons were made (the Bonferroni correction). For two categories (“public transport” and “delivery”), the achieved significance levels are lower than 0.05; a different representation was identified before and during the state of emergency. The same results were obtained within individual size categories –a different representation was identified in PT and home delivery.

4. MODELING THE ESTIMATION OF THE NUMBER OF PASSENGERS USING PUBLIC TRANSPORT

Based on data on the use of public and individual transport before and during the lockdown, it is possible to determine the impact of government measures on the willingness of passengers to choose

PT by means of logistics regression [14]. This effect can be expressed as the equivalent of an increase in the price of PT for passengers. The following formula is used to calculate the price of PT before and during the lockdown:

$$p_i = \frac{e^{\lambda V_i}}{\sum_j e^{\lambda V_j}} \quad , \qquad (1)$$

where p_i is the probability of choosing PT, λ expresses the willingness to choose a more expensive transport mode, V_i is the price of PT, and V_j is the price of the jth mode of transport.

Within these calculations, it was possible to individually select the price of individual transport modes in total and the parameter λ. To simplify the calculation, we considered the price for individual transport and the parameter λ as being equal to 1 [15].

A survey on changes in the transport behaviour of the population revealed that 358 respondents used PT before the lockdown and 251 respondents used it after the lockdown (out of a total of 1225 respondents; the entire data set was considered). Formula (1) was applied to find that the price of public passenger transport was 1.885 (dmnl) before the lockdown, while the price during the lockdown was 2.356 (dmnl). Therefore, it can be stated that the effect of the pandemic on the valuation of PT by passengers (with the value of the parameter λ = 1) will be reflected in an increase in the price by 0.471 (dmnl). Similarly, it is possible to determine the rate of valuation for individual size groups of settlements defined from the analysis of data from the survey [15, 16]. The results for these groups are summarised in Tab. 2.

Table 2

Valuation of the choice of public transport in individual size groups of municipalities

Category of municipalities	Price of PT services before the lockdown	Price of PT services during the lockdown	Price difference
Over 100,000 inhabitants	0.709415168	1.250051004	0.540635836
10–100,000 inhabitants	2.033724666	2.563975538	0.530250872
Under 10,000 inhabitants	2.512274164	2.839387518	0.327113354

Based on the determined price difference, the change in the number of passengers using PT services can be predicted in the event of a similar lockdown. With a known ratio of the number of passengers using PT to the total number of passengers before the lockdown and with the known prices of public and individual transport before the lockdown, it is possible to determine the value of the parameter λ for a specific case study [17]. For a given case study, it is possible to estimate the price of PT for passengers during a lockdown using the share of the observed price difference when using λ = 1, with the parameter λ calculated for the given case study. The result of the share is an estimate of the increase in the price of PT for passengers during a lockdown in a given case study [18]. The estimated price of PT during a lockdown is the sum of the price of PT before the lockdown and the estimated price increase during the lockdown [19]. The number of passengers using PT services during a lockdown can then be estimated. The parameter λ and the prices of PT and individual transport during a lockdown are inserted into equation (1).The result is the value of p_i, which is the ratio of the number of passengers using PT and all passengers [20, 21]. The following lines illustrate the procedure used to estimate the number of passengers in a fictitious case study.

We consider a theoretical PT line between places A and B. The number of passengers using PT before the lockdown is 250. The total number of passengers on the route is 400. The travelling cost of PT before the lockdown is CZK 25. The cost of alternative individual transport is CZK 30. Substituting these values into formula (1), we determined the value of parameter λ [22]:

$$\frac{250}{400} = \frac{e^{-25\lambda}}{e^{-25\lambda} + e^{-30\lambda}}$$

Parameter λ is equal to 0.102. We used this parameter to divide the price difference found from the data before and during the lockdown for λ = 1. Thus, we convert this difference to the difference for the parameter λ equal to 0.102 [23].

$$\frac{V_i}{\lambda} = \frac{0.471}{0.102} = 4.615$$

The result determines that the cost of a trip in PT during a lockdown would increase by CZK 4.615 from the passenger's point of view. Subsequently, it is possible to estimate the number of passengers using PT during a lockdown. This is done by inserting the travel costs in public and individual transport during a lockdown and the parameter λ into formula (1) [24]:

$$\frac{x}{400} = \frac{e^{-29.615\times 0.102}}{e^{-29.615\times 0,102} + e^{-30\times 0.102}}$$

The estimated number of passengers during a lockdown was 204 passengers (a reduction of 46 passengers). The valuation values are determined using logistics regression for PT as a whole. The survey of transport behaviour changes did not find out what specific type of means of transport in public passenger transport used or whether it was the use of PT, regional bus transport, or rail transport. At the same time, these results are related only to the population's work-related trips [25-27].

5. USE OF THE DEA METHOD FOR EVALUATING THE EFFICIENCY OF PUBLIC TRANSPORT WITH THE IMPACT OF THE COVID-19 PANDEMIC

The DEA method, which is one of the methods of multi-criteria decision-making, can be used to evaluate the technical efficiency of the so-called production units on the basis of the values of selected inputs and outputs of production units. The DEA method is suitable for determining the technical efficiency of production units that are comparable to each other (i.e. the same inputs are used to produce the same outputs), but there are differences in their performance. The units are compared with each other, and it is determined which of them are effective and which are ineffective. In the case of inefficient units, the DEA method can be used to determine how an inefficient unit should reduce its inputs or increase its outputs to become efficient.

DEA models are based on the fact that there is a set of production possibilities for any given problem, consisting of all admissible combinations of inputs and outputs. The set of production possibilities is determined by the efficient boundary. If the combination of inputs and outputs at the respective unit lies at this boundary, it is an efficient unit. If the unit is not efficient (i.e. it is not at the boundary of production possibilities), then the size of its inputs or outputs must be adjusted. DEA model solutions can be used to determine how to reduce inputs or how to increase outputs. The effective boundary can take different forms depending on whether constant or variable returns to scale in the task are considered. In the case of constant returns to scale, the α multiple of the production unit's inputs must be balanced by an increase in the production unit's outputs by the same multiple. This requirement does not apply in the case of variable returns to scale. Thus, the unit can be effective even if the relative increase in yields is lower or higher than the increase in inputs. Two basic DEA models (the CCR and BCC models) are used to evaluate the efficiency of production units. The CCR model works with constant range returns, and BCC models work with variable returns to scale. DEA models can be further divided into input- and output-oriented models. Input-oriented models determine how the inputs of inefficient production units must change to become efficient at constant outputs. Output-oriented models determine how the outputs of inefficient production units must change to become efficient at constant inputs.

The CCR input-oriented model determines the efficiency of production units on the basis of the so-called technical efficiency coefficient. In the input-oriented model, this coefficient is given as the ratio of the weighted sum of outputs and the weighted sum of inputs. The weights of inputs and outputs with the coefficient of technical efficiency are within the interval $\langle 0, 1 \rangle$, while the unit with the coefficient of technical efficiency 1 is effective. A coefficient of technical efficiency of less than 1 indicates an inefficient unit and indicates the rate of input reduction required to make the unit efficient. In the model, the unknown parameters are the weights of the inputs *i* and the weights of the outputs *j*. These weights are searched for individually for each production unit. Therefore, it is necessary to compile a separate model for each unit [28]. The mathematical model for unit *H* consists of the objective function

$$e_H = \sum_{j=1}^{n} u_{jH} y_{jH} \rightarrow MAX \quad (2)$$

and the constraint conditions

$$\sum_{i=1}^{m} v_{iH} x_{iH} = 1, \quad (3)$$

$$-\sum_{i=1}^{m} v_{iH} x_{ik} + \sum_{j=1}^{n} u_{jH} y_{jk} \leq 0, \forall k = 1,2,\dots,p, \quad (4)$$

$$u_{jH} \geq 0, \forall j = 1,2,\dots,n, \quad (5)$$

$$v_{iH} \geq 0, \forall i = 1,2,\dots,m, \quad (6)$$

where e_H is the coefficient of technical efficiency, u_{jH} and v_{iH} are the weights of inputs and outputs of the production unit H, x_{ik} and y_{jk} are the values of inputs and outputs of the production unit k, j is the total number of outputs, i is the total number of inputs, and k is the number of production units. By compiling a dual model to the primary mathematical model, we can find out which production units form sample units for the inefficient unit H. At the same time, we can find the coefficients λ_{kH} of the combination of sample units that form virtual sample units to unit H. Sample units form units whose coefficients λ have a non-zero value. The size of the inputs and outputs of a virtual unit can be calculated as a combination of inputs and outputs of the sample units [28]. The dual model consists of an objective function

$$z_H \rightarrow MIN \quad (7)$$

and the constraint conditions

$$x_{iH} z_H - \sum_{k=1}^{p} \lambda_{kH} x_{ik} \geq 0 \ \forall i = 1,2,\dots,m, \quad (8)$$

$$\sum_{k=1}^{p} \lambda_{kH} y_{jk} \geq y_{jH}, \forall j = 1,2,\dots,n, \quad (9)$$

$$\lambda_{kH} \geq 0, \forall k = 1,2,\dots,p, \quad (10)$$

where z_H is the required input reduction rate to reach the efficiency limit and λ_{kH} is the coefficient of the combination of model units for the production unit to the model for the production unit H.

The CCR output-oriented model is based on the same assumptions as the input-oriented model. The coefficient of technical efficiency is given here as the ratio of the weighted sum of outputs and the weighted sum of inputs. Weights are sought such that the value of the technical efficiency coefficient is equal to or greater than 1 [28]. The mathematical model for unit H consists of an objective function

$$e_H = \sum_{i=1}^{m} v_{iH} x_{iH} \rightarrow MIN \quad (11)$$

and of constraint conditions

$$\sum_{j=1}^{n} u_{jH} y_{jH} = 1 \quad (12)$$

$$\sum_{i=1}^{m} v_{iH} x_{ik} - \sum_{j=1}^{n} u_{jH} y_{jk} \geq 0, \forall k = 1,2,\dots,p \quad (13)$$

$$u_{jH} \geq 0, \forall j = 1,2,\dots,n \quad (14)$$

$$v_{iH} \geq 0, \forall i = 1,2,\dots,m. \quad (15)$$

The dual model is defined as follows:

$$z_H \rightarrow MAX \quad (16)$$

$$y_{jH} z_H - \sum_{k=1}^{p} \lambda_{kH} y_{jk} \leq 0 \ \forall j = 1,2,\dots,n, \quad (17)$$

$$\sum_{k=1}^{p} \lambda_{kH} x_{ik} \leq x_{iH}, \forall i = 1,2,\dots,m, \quad (18)$$

$$\lambda_{kH} \geq 0, \forall k = 1,2,\dots,p. \quad (19)$$

In the next part of the paper, the input- and output-oriented CCR model is used to evaluate the efficiency of PT in recent years using data from the example of the South Bohemian Region.

5.1. Efficiency of public transport in South Bohemia region – a case study

In this case study, the DEA method is used to determine whether the situation around the COVID-19 pandemic reduced the efficiency of PT in the South Bohemian Region. The years 2018-2020 were chosen as the production units whose efficiency will be compared. Inputs and outputs related to PT in the South Bohemian Region for the given period were determined for all years. Costs (in thousands of CZK), the number of connections, and the number of vehicles were chosen as inputs. Revenues (in thousands of CZK), traffic performance (in thousands of km), and the number of passengers (in thousands of persons) were chosen as outputs [29]. Here, the year 2020 represents a production unit, the efficiency of which could be affected by the COVID-19 pandemic. By comparing the efficiency, inputs, and outputs of this production unit with those of other units, we can determine whether the situation has affected the efficiency of PT in the South Bohemian Region. Tab. 3 shows the input and output values of all production units.

Table 3

Data for the DEA models (Source: internal materials of regional PT organiser)

Production units	Inputs			Outputs		
	Costs (thousands CZK)	Connections	Vehicles	Revenues (thousands of CZK)	Traffic performance (thousand km)	Passengers (thousand persons)
2018	916423	4895	471	428374.3	26685	17784.4
2019	1003487	4918	514	457413.8	26813	18638.4
2020	925812	4846	528	372879.1	25068	11876.1

The production unit efficiencies were calculated for the input- and output-oriented DEA models. Both models work with constant returns to scale. Frontier Analyst software was used to solve the given models. For the input-oriented model, it was found that the years 2018 and 2019 were 100% effective, while the year 2020 was 94.89% effective. Tab. 4 shows how the inputs and outputs of an inefficient unit (the year 2020) should be changed to make it efficient.

The table shows that the greatest change is recommended for the number of passengers, which should increase by 42.05% to make the 2020 production unit efficient. From this, it can be concluded that the year 2020 is inefficient compared to the remaining production units, mainly due to the low number of passengers who used PT in 2020. The principle of DEA models – where the optimal values are based on actual values from effective years and not on theoretical possibilities – is a suitable analysis method. Sources of inefficiency are searched for through an analysis of individual cost components (in the case of searching for cost reduction options). These are mainly the number of employees and the number of wages, fuel consumption, and bus depreciation [30, 31].

For the output-oriented model, it was also found that the years 2018 and 2019 were 100% efficient and that the year 2020 was 94.89%. Tab. 5 shows how the inputs and outputs of an inefficient unit (the year 2020) should be changed to make it efficient.

Table 4

Input-oriented model – target values of inputs and outputs

Inputs/outputs	Current value	Recommended value	Percentage change
Costs (thousand CZK)	925812	878486.16	-5.11 %
Number of connections	4846	4598.28	-5.11 %
Number of vehicles	528	451.13	-14.56 %
Revenues (thousand CZK)	372879	408159.86	9.46 %
Traffic performance (thousand km)	250068	250068	0 %
Passengers (thousand persons)	11876	16870.34	42.05 %

Table 5

Output-oriented model - target values of inputs and outputs

Inputs/outputs	Current value	Recommended value	Percentage change
Costs (thousand CZK)	925812	925813	0
Number of connections	4846	4846	0
Number of vehicles	528	475.43	-9.96%
Revenues (thousand CZK)	372879	430148.26	15.36%
Traffic performance (thousand km)	250068	26418.46	5.39%
Passengers (thousand persons)	11876	17779.18	49.71%

Furthermore, in this model, the greatest change is recommended for the number of passengers. Here, the number of passengers should be increased by 49.71% to make the production unit of the year 2020 efficient. This confirms the results obtained by the input-oriented model. The year 2020 is inefficient mainly due to the low number of passengers.

6. CONCLUSIONS

A questionnaire survey was distributed among the inhabitants of the CR to identify changes in modes of transport used for regular journeys to work, school, or for shopping. Other aspects related to the patterns of citizen transport behaviour were also investigated. A total of 3,148 people responded to the questionnaire was responded by. Approximately 12% of the respondents (the economically active population) changed their preferred mode of transport because of the state of emergency and government restrictions. In particular, a shift from PT to private motor vehicle transport was observed. The results of the McNemar test confirmed the existence of a statistically significant difference in the representation of the five categories of transportation (by car as a driver, by car as a passenger, by PT, by bicycle, and on foot) before and during the state of emergency. However, due to the nature of the survey, it was not possible to statistically evaluate whether the changes in the categories of these modes of transport will be permanent.

Moreover, in the economically active population, there was a change in the frequency of journeys in 53.9% of cases (most of the inhabitants did not commute to work for various reasons, or they commuted less often). Most students did not commute to schools because of school closures. For this reason, this category of respondents was not considered in the evaluation of changes in modes of transport used for commuting to school. Urban dwellers in the CR continued using passenger motor vehicles for commuting to work and did so even more often than before the lockdown. This significantly reduced the share of PT in the overall modal split. However, it did not have any visible effect on the roads since the citizens largely limited their mobility for various reasons. To some extent, the number of citizens who decided to use "active transport" increased. In the case of modes of transport used for shopping, citizens' transport behaviour did not differ according to the size of the municipalities they lived in. The difference between citizen transport behaviour in individual size categories of municipalities is statistically insignificant ($\chi2 = 5.28$, df = 2, $p < 0.071$).

The McNemar test showed a statistically significant difference within the entire sample (this outcome was similar even for individual size categories of municipalities) among respondents who used PT for shopping (a decrease) and respondents who had their groceries delivered to their homes (an increase). The survey also showed that the respondents preferred small shops close to their homes and that there was a significant increase in online purchases of food from shops that offered home delivery. The authors also proposed a method for estimating the number of passengers by applying linear regression based on the change in papulation transport behaviour caused by a pandemic. It was found that linear regression is applicable for estimating the number of passengers based on data from the conducted survey. The DEA models show that the only inefficient unit is the year 2020, which is the only investigated year that was affected by the COVID-19 situation. The efficiency of PT in the South Bohemian Region in 2020 was 5.11% lower than in other years. The lower efficiency was due to a significant decrease in the number of passengers; however, the inputs of the production unit remained approximately the same as in previous years. It can be assumed that the low number of passengers in 2020 was due to the COVID-19 situation. Based on this, it can be stated that the COVID-19 situation negatively affected the efficiency of PT in the South Bohemian Region.

The results obtained through the questionnaire survey can be further used for research in other areas of transport or other socio-economic or socio-demographic areas. The results are in line with the results of other studies on societal changes in the area of mobility conducted in other countries where lockdowns and various government measures were implemented to prevent the spread of COVID-19.

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References

1. Shibayama, T. & Sandholzer, F. & Laa, B. & Brezina, T. Impact of COVID-19 lockdown on commuting: a multi-country perspective. *European Journal of Transport and Infrastructure Research*. 2021. Vol. 21. P. 70-93. DOI: https://doi.org/10.18757/ejtir.2021.21.1.5135.
2. Awad-Núñez, S. & Julio, R. & Gomez, J. & et al. Post-COVID-19 travel behaviour patterns: impact on the willingness to pay of users of public transport and shared mobility services in Spain. *Eur.* Transp. Res. Rev. 2021. Vol. 13. No. 1. P. 20. DOI: https://doi.org/10.1186/s12544-021-00476-4.
3. Ceder, A. Urban mobility and public transport: future perspectives and review. *International Journal of Urban Sciences*. 2021. Vol. 25. No 4. P. 455-479. DOI: https://doi.org/10.1080/12265934.2020.1799846.
4. Bucsky, P. Modal share changes due to COVID-19: The case of Budapest. *Transp. Res. Interdiscip. Perspect*. 2020. Vol. 8. Art. No. 100141. P. 1-5. DOI: https://doi.org/10.1016/j.trip.2020.100141.
5. Barbarossa, L. The Post Pandemic City: Challenges and Opportunities for a Non-Motorized Urban Environment. An Overview of Italian Cases. *Sustainability.* 2020. Vol. 12. No. 17. P. 1-19. DOI: https://doi.org/10.3390/su12177172.
6. Przybylowski, A. & Stelmak, S. & Suchanek, M. Mobility Behaviour in View of the Impact of the COVID-19 Pandemic – Public Transport Users in Gdansk Case Study. *Sustainability*. 2021. Vol. 13. No. 1. P. 1-12. DOI: https://doi.org/10.3390/su13010364.
7. Pawar, D.S. & Yadav, A.K. & Akolekar, N. & Velaga, N.R. Impact of physical distancing due to novel coronavirus (SARS-CoV-2) on daily travel for work during transition to lockdown. *Transportation Research Interdisciplinary Perspectives*. 2020. Vol. 7. Art. No. 100203. P. 1-9. DOI: https://doi.org/10.1016/j.trip.2020.100203.
8. Deponte, D. & Fossa, G. & Gorrini, A. Shaping space for ever-changing mobility. Covid-19 lesson learned from Milan and its region. *TeMA - Journal of Land Use, Mobility and Environment.* 2020. Special Issue. Covid-19 vs City-20. P. 133-149. DOI: https://doi.org/10.6092/1970-9870/6857.
9. Kolic, B. & Dyer, J. Data-driven modeling of public risk perception and emotion on Twitter during the Covid-19 pandemic. *Appl. Netw. Sci*. 2020. Vol. 5. P. 1-32. DOI: https://doi.org/10.1007/s41109-020-00334-7.
10. Gottwald, D. & Svadlenka, L. & Lejskova, P. & Pavlisova, H. Human Capital as a Tool for Predicting Development of Transport and Communications Sector: The Czech Republic Perspective. *Communications – Scientific Letters of the University of Zilina*. 2017. Vol. 19. No. 4. P. 50-56.
11. Budd, L. & Ison, S. Responsible Transport: A post-COVID agenda for transport policy and practice. *Transportation Research Interdisciplinary Perspectives*. 2020. Vol. 6. Art. No. 100151. P. 1-5. DOI: https://doi.org/10.1016/j.trip.2020.100151.
12. Caban, J. & Drozdziel, P. & et al. Road Traffic Safety in Poland, Slovakia and Czech Republic-Statistic Analysis. In: *12th International Science-Technical Conference Automotive Safety*. 2020. P. 1-7. DOI: 10.1109/AUTOMOTIVESAFETY47494.2020.9293507.
13. Vojtek, M. & Kendra, M. & Zitrický, V. & Široký, J. Mathematical approaches for improving the efficiency of railway transport. *Open Engineering*. 2021. Vol. 10. No. 1. P. 57-63. DOI: https://doi.org/10.1515/eng-2020-0008.
14. Ben-Akiva, M. & et al. Extended Framework for Modeling Choice Behavior. *Marketing Letters*. Vol. 10. No. 3. P. 187-203. DOI: https://doi.org/10.1023/A:1008046730291.
15. Fedorko, G. & Heinz, D. & Molnár, V. & Brenner, T. Use of mathematical models and computer software for analysis of traffic noise. *Open Engineering*. 2020. Vol. 10. No. 1. P. 129-139. DOI: 10.1515/eng-2020-0021.
16. Hlatká, M. & Kampf, R. & Gross, P. Optimisation of Distribution Routes: A Case Study. *Communications – Scient. Letters of the Univ. of Žilina*. 2021. Vol. 23. No. 1. P. 62-73. DOI: https://doi.org/10.26552/com.C.2021.1.A62-A73.

17. Brídziková, M. & Konečný, V. & Hammer, J. & Abramovic, B. Demand specifics of disabled persons and persons with reduced mobility for bus transport. Case of regional bus transport in Slovakia. *The Archiv. of Automot. Engineer. – Archiwum Motoryzacji*. 2020. Vol. 87. No. 1. P. 81-95. DOI: https://doi.org/10.14669/AM.VOL87.ART7.
18. Černá, L. & Zitrický, V. & Abramović, B. Methodical Manual for a Set of Transport Regulations in Railway Passenger Transport. *LOGI – Scient. J. on Transp. and Logist.* 2020. Vol. 11. No. 1. P. 13-24. DOI: https://doi.org/10.2478/logi-2020-0002.
19. Hitka, M. & Štarchoň, P. & Caha, Z. & Lorincová, S. & Sedliačiková, M. The global health pandemic and its impact on the motivation of employees in micro and small enterprises: a case study in the Slovak Republic. *Economic Research-EkonomskaIstraživanja*. 2021. P. 1-22. DOI: https://doi.org/10.1080/1331677X.2021.1902365.
20. Poliak, M. & Tomicová, J. & Reuter N. Impact of indirect user participation on public transport financing. *The Archiv. of Automot. Engineer. – ArchiwumMotoryzacji*. 2019. Vol. 86. No. 4. P. 65-77. DOI: https://doi.org/10.14669/AM.VOL86.ART5.
21. Parker, M.E.G. & Li, M. & Bouzaghrane, M.A. & Obeid, H. & Hayes, D. & Frick, K.T. & Rodríguez, D.A. & Sengupta, R. & Walker, J. & Chatman, D.G. Public transit use in the United States in the era of COVID-19: Transit riders' travel behavior in the COVID-19 impact and recovery period. *Transport Policy*. 2021. Vol. 111. P. 53-62. DOI: https://doi.org/10.1016/j.tranpol.2021.07.005.
22. Nwokedi, T.C. & Okoroji, L.I. & Okonko, I. & Ndikom, O.C. Estimates of Economic Cost of Congestion Travel Time Delay between Onne-Seaport and Eleme-Junction Traffic Corridor. *LOGI – Scient. J. on Transp. and Logist.* 2020. Vol. 11. No. 2. P. 33-43. DOI: 10.2478/logi-2020-0013.
23. Tiikkaja, H. & Viri, R. The effects of COVID-19 epidemic on public transport ridership and frequencies. A case study from Tampere, Finland. *Transportation Research Interdisciplinary Perspectives*. 2021. Vol. 10. Art. No. 100348. P. 1-7. DOI: https://doi.org/10.1016/j.trip.2021.100348.
24. Ľupták, V. & Stopková, M. & Jeřábek, K. Comparative analysis in terms of environmental impact assessment between railway and road passenger transport operation: A case study. In: *2019 TransportMeans – Proceedings of the International Conference*. October 2019. P. 1330-1334. DOI: 10.1504/IJSA.2020.108088.
25. Min, B. & Lee, G. & Kim, S. Effects of land-use characteristics on transport mode choices by purpose of travel in Seoul, South Korea, based on spatial regression analysis. *Sustainability*. 2021. Vol. 13. No. 4. P. 1-22. DOI: https://doi.org/10.3390/su13041767.
26. Jiao, F. & Huang, L. & Song, R. & Huang, H. An improved STL-LSTM model for daily bus passenger flow prediction during the covid-19 pandemic. *Sensors*. 2021. Vol. 21. No. 17. Art. No. 5950. DOI: https://doi.org/10.3390/s21175950.
27. Droździel, P. & Wińska, M. & Madleňák, R. & Szumski, P. Optimization of the position of the local distribution centre of the regional post logistics network. *Transport Problems*. 2017. Vol. 12. No. 3. P. 43-50. DOI: 10.20858/tp.2017.12.3.4.
28. Šubrt, T. *Ekonomicko-matematické metody - 3. Vydání.* Plzeň: Aleš Čeněk s.r.o. 2019. ISBN 978-80-7380-762-7. [In Czech*: Economic-mathematical methods* - 3. revised and expanded edition. Plzeň: AlešČeněk publishing. 2019. ISBN 978-80-7380-762-7].
29. Caban, J. & Voltr O. A Study on the use of eco-driving technique in city traffic. *The Archiv. of Automot. Engineer. – Archiwum Motoryzacji*. 2020. Vol. 93. No. 3. P. 15-25. DOI: 10.14669/AM.VOL93.ART2.
30. Kampf, R. & Čejka, J. & Telecký, M. Applicability of the DEA method on the transport undertakings in selected regions. *Communications: scientific letters of the University of Žilina*. 2016. Vol. 18. No. 2. P. 129-132. ISSN: 1335-4205.
31. Poliak, M. & Poliaková, A. & Jaskiewicz, M. & Hammer, J. Potreba integriranja javnog putnickog prometa. [In Croatian: The need of public passenger transport integration]. *Ekonomski Pregled*. 2020. Vol. 71. No. 5. P. 512-530. DOI: 10.32910/ep.71.5.4.

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