



## Traffic behavior during the COVID-19 pandemic and its potential consequences for passenger rail transport in the example of selected European countries

Agnieszka Barczak<sup>1</sup>✉, Sabina Kauf<sup>2</sup>

<sup>1</sup>  <https://orcid.org/0000-0001-7584-7183>

<sup>2</sup>  <https://orcid.org/0000-0002-5978-4490>

<sup>1</sup> West Pomeranian University of Technology in Szczecin, Faculty of Economics,  
Department of Management and Marketing  
31 Janickiego St., 71-270 Szczecin, Poland

<sup>2</sup> University of Opole, Institute of Management and Quality, Department of Logistics and Marketing  
45 a Ozimska St., 45-058 Opole, Poland

e-mail: <sup>1</sup>agnieszka-barczak@zut.edu.pl; <sup>2</sup>skauf@uni.opole.pl

✉ corresponding author

**Keywords:** combined forecasts, communication behavior, COVID-19 pandemic, forecast, passenger rail transport, the future of rail transport

**JEL Classification:** C53, L92, R41, R42

### Abstract

The COVID-19 pandemic has caused vast changes in the functioning of societies and economies, including restrictions on the use of rail transportation. As a result, the number of passengers has declined, and despite the lifting of restrictions, it is still difficult to estimate when and if passenger rail traffic will return to its pre-pandemic state. Therefore, it seems important to consider the following: how the pandemic has affected the transportation behavior patterns of residents and, above all, what should be done to encourage passengers to use rail transportation more often, which is more environmentally friendly and reduces greenhouse gas emissions. Thus, it seems important to consider what the “new normal” in rail transportation should look like. This article analyzes the number of passengers traveling by rail in eight European countries. This work considers quarterly data for 2013–2019, combined passenger forecasts for 2020–2021, and annual forecasts of rail passenger traffic until 2025 built using data for 2012–2021.

### Introduction

The COVID-19 pandemic was a global humanitarian crisis that had a negative impact on many industries and sectors of the economy. The lockdown, which was announced worldwide, caused a drastic reduction in the mobility of the population by all means of travel. As a result of the introduction of remote work, mandatory movements were reduced, and optional ones were essentially eliminated. Messages were disseminated that it was particularly dangerous to travel by bus, streetcar, or train. Passenger rail operators, who found themselves

in perhaps the largest crisis in their history, were particularly hard hit by the consequences. Although sanitary restrictions in Europe and many other countries around the world have been lifted for more than a year now, passenger rail traffic has still not been fully restored. Thus, rail operators have faced challenges arising from the population’s changed transportation behavior. Some opportunities for the railroads arise due to the growing environmental sensitivity of the population. Research conducted by McKinsey in 2021 shows that consumer preferences are shifting toward more sustainable travel, as 61 % of respondents said they want more sustainable

travel in the future (Ahmad et al., 2022). In addition, the share of car transportation in Europe is expected to decrease by about 70 % over the next ten years (Chapuis, Delporte & Lotz, 2021).

Not insignificant, too, are the actions of governments in pursuit of ambitious targets for reducing greenhouse gas emissions. As a result, they are taking a number of measures to promote sustainable mobility. Most of these include simulation packages to revitalize the economy and, in particular, to modernize rail infrastructure and decarbonize transportation. For example, the European Green Deal assumes spending of €87 billion to modernize rail infrastructure (Chapuis, Delporte & Lotz, 2021).

Considering that rail accounts for only 0.4 % of greenhouse gas emissions in the European Union (this is drastically less than road transport, where the percentage is 71 %), it has the ability to transport a large number of passengers faster than by road and, with increased travel comfort, it has the potential to become one of the preferred transportation choices in the future. Not only is it environmentally friendly and energy efficient, but it is also the only mode of transportation that almost consistently reduces CO<sub>2</sub> emissions. Despite its significant advantages, rail faces problems mainly related to relatively high prices, lack of punctuality and reliability, insufficient

line density, and difficulties in organizing door-to-door travel. Nevertheless, in the context of the European Union's forward-looking programs, rail has a key role to play. It is the most sustainable and environmentally friendly mode of transportation, and it is an integral part of the sustainable transport development strategy and a way to transform it towards green mobility.

With the above in mind, this study attempts to answer several questions: (1) how the pandemic affected the population's travel behavior patterns, (2) how the rail transportation situation evolved during the pandemic, and (3) to what extent the population's behavior toward rail travel may change, and (4) what a mobility paradigm that considers future crises should look like. To this end, the number of passengers in selected European countries during the pandemic was analyzed, and forecasts for the post-pandemic period were determined. These can become a starting point for proposing a set of actions that rail operators could take to not only recover passengers lost by the pandemic but also to attract new ones, developing rail as a viable alternative to other modes of transportation.

Countries with at least 193,569 thousand rail passengers in 2019 were selected for the analysis. These are Spain, France, Italy, Switzerland, and Germany

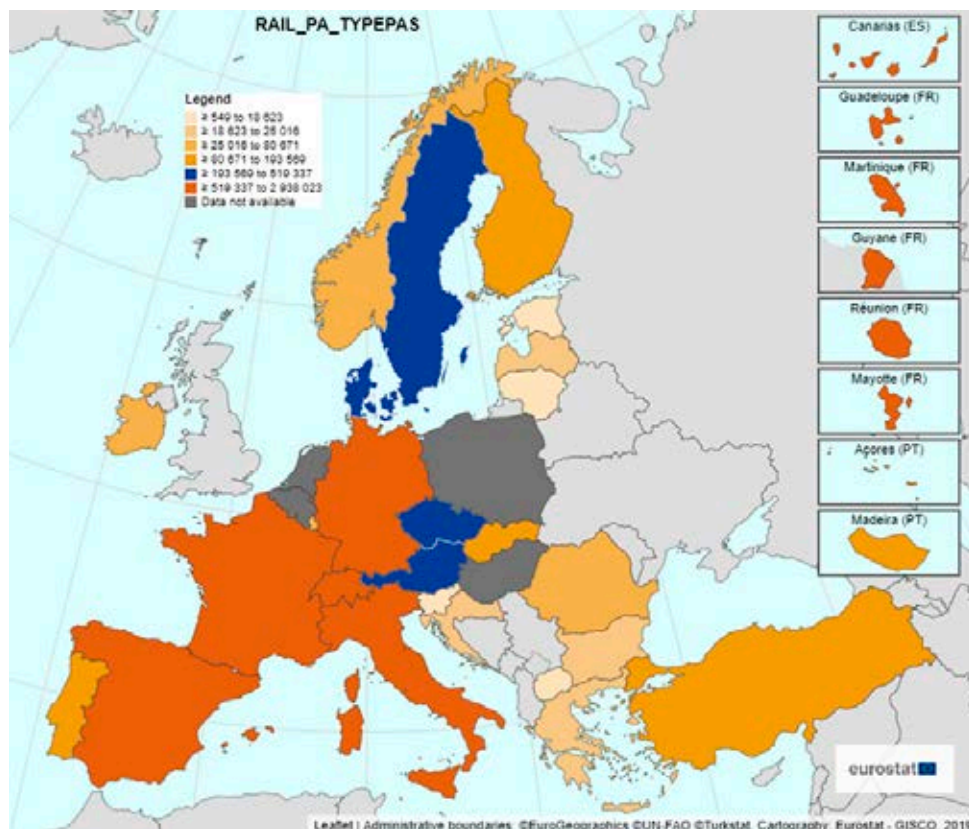


Figure 1. Number of rail passengers in European countries in 2019 (in thousands) (Eurostat, 2023)

(dark orange color in Figure 1), Austria (no quarterly data, so it was excluded from the analysis), Czechia, Denmark, and Sweden (blue color in Figure 1).

Compared to 2019, passenger rail traffic in the surveyed countries saw significant declines in the number of passengers served in 2020 and 2021. As Table 1 indicates, in almost all countries, these declines exceeded 30 %. This is why it is so important to estimate the losses that have been incurred in passenger transportation of this branch as a result of the pandemic.

**Table 1. Dynamics of changes in the number of passengers year on year (own study based on Eurostat data)**

Country	2020/2019	2021/2019
Spain	-47.46 %	-35.51 %
France	-42.79 %	-29.32 %
Italy	-56.71 %	-45.62 %
Switzerland	-32.22 %	-32.05 %
Germany	-38.35 %	-39.89 %
Czechia	-33.50 %	-31.09 %
Denmark	-35.19 %	-35.27 %
Sweden	-36.07 %	-37.83 %

Graphical and quantitative analysis of the time series showed that the series is characterized by the presence of seasonality. On this basis, forecasting methods were selected, on the basis of which combined forecasts were built. Such forecasting methods involve Fourier spectral analysis, exponential smoothing models, univariate period trends, and seasonality indicators. This was based on quarterly data from 2013–2019, and the results of the combined forecasts were compared with quarterly data from 2020–2021. This made it possible to indicate the differences, using the relative error of the ex-post forecast, in passenger rail transport resulting from the restrictions introduced as a result of the COVID-19 pandemic.

Above this, three annual forecasts up to 2025 were set for each country. The first was built using a trend function, characterized by the best fit to the data, based on actual data for 2012–2019 supplemented by projected data for 2020–2021. The second forecast was built based on the actual average growth in the number of passengers over the entire pre-pandemic period studied (2012–2019) and the assumption that, by 2025, this growth will be at the same level every year. The third forecast was made based on the assumption that the number of passengers will grow by 10 % year on year compared to the previous year.

## Research methodology

Since estimating forecasts by different methods results in various values, combined forecasts were used. Combined forecasts are determined by different methods, but, for the purpose of this study, a weighted average of individual forecasts determined using different methods was chosen (Perzyńska, 2017). According to Winkler and Makridakis (1983), “An alternative to the traditional approach is to aggregate information from different forecasting methods by aggregating forecasts. This eliminates the problem of having to select a single method and rely exclusively on its forecasts”. An overview related to combined forecasting can be found, for example, in the work of Mancuso and Werner (2013).

For the construction of combined forecasts, mean percentage absolute error (MAPE) was used, which informs about the average size of forecast errors expressed as a percentage of the actual values of the forecast variable. It is determined from the following formula:

$$\text{MAPE} = \frac{1}{m} \sum_{t=1}^m \left| \frac{y_t - y_t^p}{y_t} \right| \cdot 100 \quad (1)$$

As mentioned earlier, a weighted average method was used, where the weights were inversely proportional to the ex-post error. Such a procedure allows us to increase the influence of a more accurate model (in the sense of the error of expired forecasts) on the final value of the combined forecast.

The first method used to build combinational forecasts is Fourier spectral analysis (i.e., a harmonic analysis), the methodology of which is described in, among others, a previous paper (Barczak et al., 2022). The construction of the model is based on the summation of so-called harmonics (sine and cosine functions with a given period). The first harmonic has a period equal to the length of the test period, the second half of this period, and so on. For  $n$  observations in a time series, the number of all harmonics corresponds to the value of  $n/2$ .

The notation of the periodic component model is as follows:

$$y_t = \alpha_0 + \sum_{i=1}^{\frac{n}{2}} \left[ \alpha_i \sin\left(\frac{2\pi}{n} it\right) + \beta_i \cos\left(\frac{2\pi}{n} it\right) \right] \quad (2)$$

where  $i$  signifies the harmonics number and  $\alpha_0$ ,  $\alpha_i$ , and  $\beta_i$  are the relevant parameters.

Parameters  $a_0$ ,  $a_i$ , and  $b_i$ , which are the ratings of the parameters of the equation, are estimated with

the following formulas using the method of least squares:

$$a_0 = \frac{1}{n} \sum_{i=1}^n y_i \quad (3)$$

$$a_i = \frac{2}{n} \sum_{i=1}^n y_i \sin\left(\frac{2\pi}{n} it\right), \quad i = 1, 2, \dots, \frac{n}{2} - 1 \quad (4)$$

$$b_i = \frac{2}{n} \sum_{i=1}^n y_i \cos\left(\frac{2\pi}{n} it\right) \quad (5)$$

For the last  $n/2$  harmonic, the parameter  $a_{n/2}$  takes the value of zero, and the evaluation value of the parameter  $b_{n/2}$  is determined according to the following formula:

$$b_{\frac{n}{2}} = \frac{1}{n} \sum_{i=1}^n y_i \cos(\pi t) \quad (6)$$

Fourier spectrum analysis refers to the study of fluctuations around the average level, which is represented by the parameter  $a_0$ . When there is a clear trend in the studied time series, the model takes the form:

$$y_t = f(t) + \sum_{i=1}^{\frac{n}{2}} \left[ \alpha_i \sin\left(\frac{2\pi}{n} it\right) + \beta_i \cos\left(\frac{2\pi}{n} it\right) \right] \quad (7)$$

where  $f(t)$  denotes the trend function.

In the final form of the model, only those harmonics that make a significant contribution to explaining the variance of the variable under study are included. For this purpose, the following equation is used:

$$\frac{d_i^2}{2s^2} \quad \text{for } i = 1, 2, \dots, \frac{n}{2} - 1 \quad (8)$$

allowing us to determine what part of the variance of the variable under study is explained by individual harmonics.

For the last harmonic, this percentage is found from the following formula:

$$\frac{d_i^2}{s^2} \quad \text{for } i = \frac{n}{2} \quad (9)$$

where  $s^2$  represents the variance of the variable under study and  $d_i^2$  is the value determined from the following equation:

$$d_i^2 = a_i^2 + b_i^2 \quad \text{for } i = 1, 2, \dots, \frac{n}{2}.$$

Another of the methods used is exponential smoothing. This involves smoothing the time series of the forecast variable using a weighted moving average, and the weights are determined according

to the exponential law. In the process of exponential smoothing, various models can be used, which are adjusted to the type of components of the forecast time series. For this reason, the paper does not describe the individual models focusing only on their analysis; a comprehensive description of the method can be found in various previous publications (Brown & Meyer, 1961; Montgomery, Johnson & Gardiner, 1978; Billah et al., 2006; Ostertagova & Ostertag, 2011, 2012; Oral, 2019; Kovačević, Rebić & Kurušić, 2021).

The third of the methods used to build the combined forecasts is the one-name period trend method. This method is based on the estimation of the parameters of the analytical trend function with division into individual cycle phases. The forecast is obtained by extrapolating an estimated trend function for each phase of the cycle (Barczak, 2016, 2021).

The last method used is the method of seasonality indicators (the description of the method is taken from a previous paper (Barczak, 2015, 2021)). The method of determining the forecast depends on the type of seasonal fluctuations, which may be multiplicative or additive. In the analyzed time series, seasonal fluctuations are additive in nature (additive fluctuations refer to a situation in which there are constants in terms of absolute value deviation of the level of the analyzed phenomenon from the average level or trend in individual seasonality cycle sub-periods); therefore, the description of the method is limited to the formulas used in this case.

The applied method of determining the seasonality indicators is based on the quotient of empirical values and the value of the trend. The average index for homonymous periods is found successively. Otherwise, the quotient of the mean homonymous periods by the average trend value of the homonymous periods is used as follows:

$$S_i = \frac{\sum y_i}{n \hat{y}_i} \cdot 100 \quad \text{or} \quad S_i = \frac{\sum \bar{y}_i}{\hat{y}_i} \cdot 100 = \frac{\sum \bar{y}_i}{\sum \hat{y}_i} \cdot 100 \quad (10)$$

where  $S_i$  is the seasonality index for the  $i$ -th seasonality cycle subperiod,  $y_i$  is the empirical value of the period variable  $i$ ,  $\bar{y}_i$  is the mean empirical value of the variable of the homonymous periods,  $\hat{y}_i$  is the value of the trend of the period  $i$ ,  $\hat{y}_i$  is the average value of the trend of the homonymous periods, and  $n$  is the number of homonymous periods.

Seasonality indicators must meet the following condition:

$$\sum_{i=1}^d S_i = d \quad (11)$$

If it is not met, it is necessary to determine the correction factor, i.e.:

$$k = \frac{d}{\sum_{i=1}^d S_i} \tag{12}$$

where  $d$  signifies the number of sub-periods in the cycle.

This coefficient allows for the transformation of raw (uncleaned) seasonal indicators into indicators purified using the following formula:

$${}_k S_i = k \cdot S_i \tag{13}$$

If known, the measures of seasonal fluctuations and the trend function of the studied phenomenon allow for obtaining forecasts. For additive seasonal fluctuations, in order to obtain a forecast for the period  $t = T$ , the following formula is applied:

$$y_T^P = \hat{y}_T + {}_k S_i \tag{14}$$

where  $y_T^P$  is the forecast for the period  $t = T$  and  $\hat{y}_T$  is the value of the estimated trend function.

Once the combined forecasts are made, the relative differences between actual and forecast values were determined using the relative error of the ex-post forecast:

$$\gamma = \frac{y_t - y_t^P}{y_t} \cdot 100\% \tag{15}$$

where  $y_t$  is the actual value of the variable realization and  $y_t^P$  is the forecast value of the variable.

### The situation in the rail transport market during the pandemic – research results

Table 2 shows the obtained MAPE forecast error values for each country and the forecasting method.

**Table 2. Mean absolute percentage error (MAPE) for the individual forecasting methods included in the combined forecast (own compilation based on Eurostat data)**

Country	Mean absolute percentage error (MAPE)			
	Fourier spectral analysis	Exponential smoothing method	One-period trend method	Method of seasonality indices
Spain	0.9762	0.9305	1.0350	1.0295
France	0.7983	0.7420	0.8220	0.8233
Italy	1.3390	1.3121	1.3687	1.3717
Switzerland	0.6536	0.6710	0.7188	0.6851
Germany	0.8007	0.7858	0.7980	0.7964
Czechia	0.5827	0.5034	0.5699	0.5740
Denmark	–	0.6553	0.5439	0.6983
Sweden	0.7473	0.7307	0.7500	0.7307

In the case of Denmark, the harmonics obtained by Fourier spectral analysis did not significantly explain the variance of the variable under study. Therefore, this method was not considered when creating combined forecasts for this country.

**Table 3. Actual value and combined forecast of passenger volume with relative ex post forecast error, assuming that there was no COVID-19 pandemic in 2020 (own compilation based on Eurostat data)**

	Actual number of passengers	Value of combined forecast	Relative ex post forecast error
Spain			
IQ	131 495	159 747	–21.49 %
IIQ	35 048	153 194	–337.10 %
IIIQ	77 545	150 403	–93.96 %
IVQ	85 390	161 274	–88.87 %
France			
IQ	244 776	326 311	–33.31 %
IIQ	81 365	311 782	–283.19 %
IIIQ	205 988	310 969	–50.96 %
IVQ	191 724	332 700	–73.53 %
Italy			
IQ	149 261	219 918	–47.34 %
IIQ	45 978	221 276	–381.27 %
IIIQ	98 159	205 542	–109.40 %
IVQ	88 977	230 323	–158.86 %
Switzerland			
IQ	112 214	130 683	–16.46 %
IIQ	53 871	133 513	–147.84 %
IIIQ	96 025	135 119	–40.71 %
IVQ	83 057	138 433	–66.67 %
Germany			
IQ	620 036	736 053	–18.71 %
IIQ	295 000	741 646	–151.41 %
IIIQ	480 000	745 270	–55.26 %
IVQ	406 081	765 341	–88.47 %
Czechia			
IQ	38 988	46 806	–20.05 %
IIQ	25 934	49 581	–91.18 %
IIIQ	39 053	48 337	–23.77 %
IVQ	25 167	48 107	–91.15 %
Denmark			
IQ	42 110	49 566	–17.71 %
IIQ	23 303	50 561	–116.97 %
IIIQ	36 991	49 008	–32.49 %
IVQ	31 493	53 482	–69.82 %
Sweden			
IQ	63 109	66 611	–5.55 %
IIQ	30 624	67 001	–118.79 %
IIIQ	38 255	64 571	–68.79 %
IVQ	37 175	70 691	–90.16 %

Tables 3 and 4 summarize the quarterly values of actual passengers carried in 2020 and 2021, along with the combined forecast values for these periods and the relative differences between actual and forecast values using the relative ex-post forecast error.

**Table 4. Actual value and combined forecast of passenger volume with relative *ex post* forecast error, assuming that there was no COVID-19 pandemic in 2021 (own compilation based on Eurostat data)**

	Actual number of passengers	Value of combined forecast	Relative ex post forecast error
Spain			
IQ	81 867	161 308	-97.04 %
IIQ	100 547	154 083	-53.24 %
IIIQ	99 937	155 359	-55.46 %
IVQ	122 041	161 604	-32.42 %
France			
IQ	192 935	329 586	-70.83 %
IIQ	196 795	314 128	-59.62 %
IIIQ	229 212	308 181	-34.45 %
IVQ	275 455	331 957	-20.51 %
Italy			
IQ	84 136	221 002	-162.67 %
IIQ	111 509	221 504	-98.64 %
IIIQ	127 425	209 204	-64.18 %
IVQ	157 248	232 136	-47.62 %
Switzerland			
IQ	72 489	137 400	-89.55 %
IIQ	78 581	140 751	-79.12 %
IIIQ	93 383	143 115	-53.26 %
IVQ	101 544	145 944	-43.72 %
Germany			
IQ	322 700	750 950	-132.71 %
IIQ	392 500	757 446	-92.98 %
IIIQ	524 300	759 355	-44.83 %
IVQ	516 600	774 757	-49.97 %
Czechia			
IQ	22 715	47 534	-109.26 %
IIQ	32 512	49 637	-52.67 %
IIIQ	38 820	49 023	-26.28 %
IVQ	39 774	48 505	-21.95 %
Denmark			
IQ	19 656	48 697	-147.75 %
IIQ	32 027	48 918	-52.74 %
IIIQ	39 862	48 076	-20.61 %
IVQ	42 190	53 722	-27.33 %
Sweden			
IQ	31 339	68 885	-119.81 %
IIQ	35 757	69 260	-93.70 %
IIIQ	42 645	68 442	-60.49 %
IVQ	54 750	72 158	-31.79 %

In all quarters in both 2020 and 2021, the number of rail passengers transported was lower than forecast values in all countries. The largest differences were recorded in the second quarter of 2020 and in the first quarter of the following year.

### Forecast of the number of rail passengers until 2025

The first forecast was built using actual data for 2012–2019 supplemented by forecast data (from Tables 3 and 4) for 2020–2021. Within the parentheses are given the trend functions characterized by the best fit to the data and basic measures of fit. As mentioned earlier, the second forecast was determined on the basis of average passenger growth in 2012–2019, assuming annual growth at the same level. The third forecast assumes an annual 10 % increase in the number of passengers.

Figure 2 shows the forecasts for Czechia. The first forecast was built based on a linear trend ( $y_t = 2801.6303t + 167640.7333$ ,  $R^2 = 0.9397$ ,  $V_S = 1.25\%$ ). The second assumes an annual increase of 1.66 % in the number of passengers. There are clear differences between the forecast results that were obtained. If the increase in the number of passengers remains at the same level as before the pandemic (1.66 %) or is maintained at 10 % annually, the number of passengers traveling by rail will not reach pre-pandemic levels by 2025.

Figure 3 shows the forecasts for Denmark. The first forecast was built based on a parabolic trend ( $y_t = -431.9167t^2 + 4257.7742t + 199263.6333$ ,  $R^2 = 0.8099$ ,  $V_S = 0.91\%$ ). The second assumes an annual increase of 0.34 % in the number of passengers. Again, the differences between the obtained forecast results are clearly visible. If passenger growth remains at the same level as before the pandemic (0.34 %), by 2025, the number of passengers traveling by rail will not reach pre-pandemic levels. On the other hand, assuming an annual 10 % increase, the number of passengers will return to the pre-pandemic level in 2024 and surpass it the following year.

Figure 4 shows the forecasts for Germany. The first forecast was built based on a linear trend ( $y_t = 53092.3515t + 2512979.4667$ ,  $R^2 = 0.9856$ ,  $V_S = 0.73\%$ ). The second assumes an annual increase of 1.97 % in the number of passengers. Again, the differences between the obtained forecast results are clearly visible. If the increase in the number of passengers remains at the same level as before the pandemic (1.97 %) or increases by 10 % from

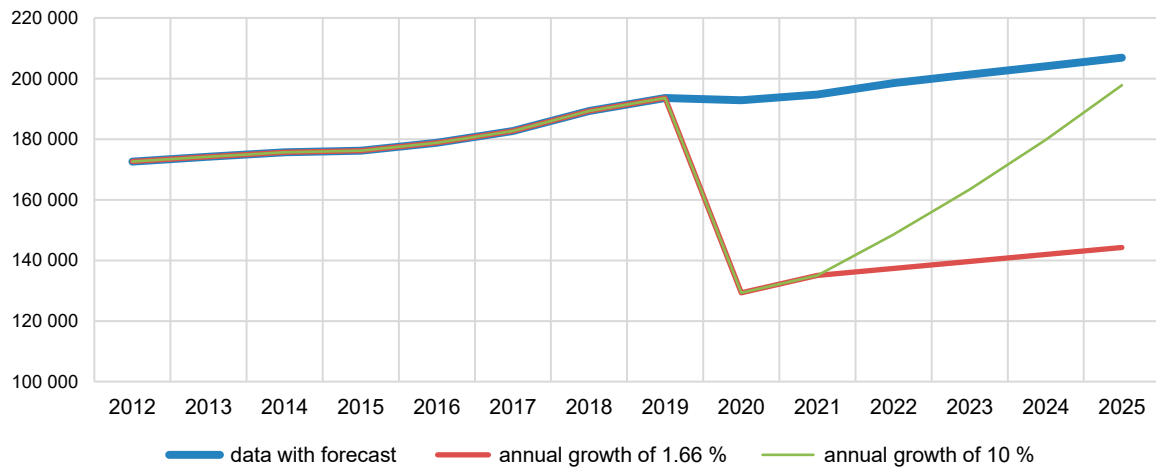


Figure 2. Forecasts for Czechia (own compilation based on Eurostat data)

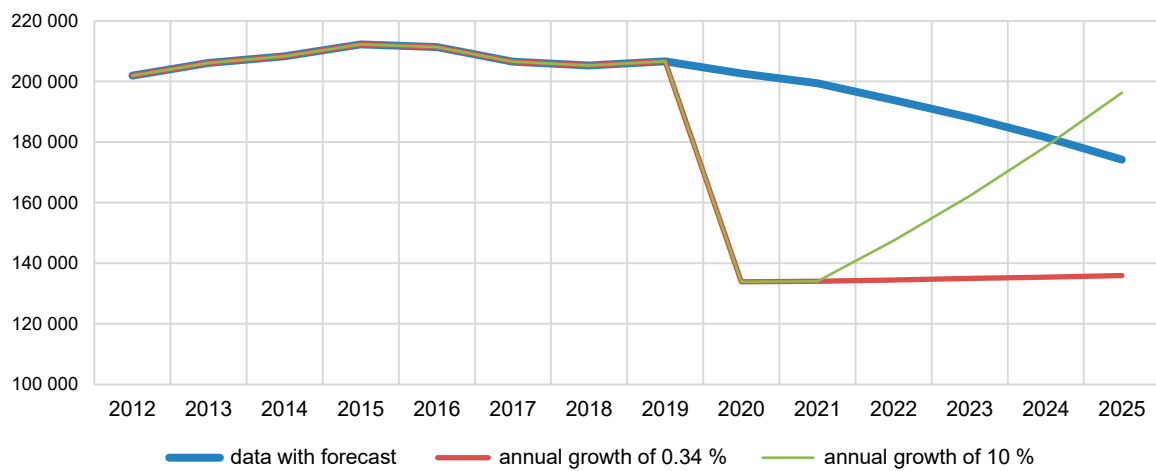


Figure 3. Forecasts for Denmark (own compilation based on Eurostat data)

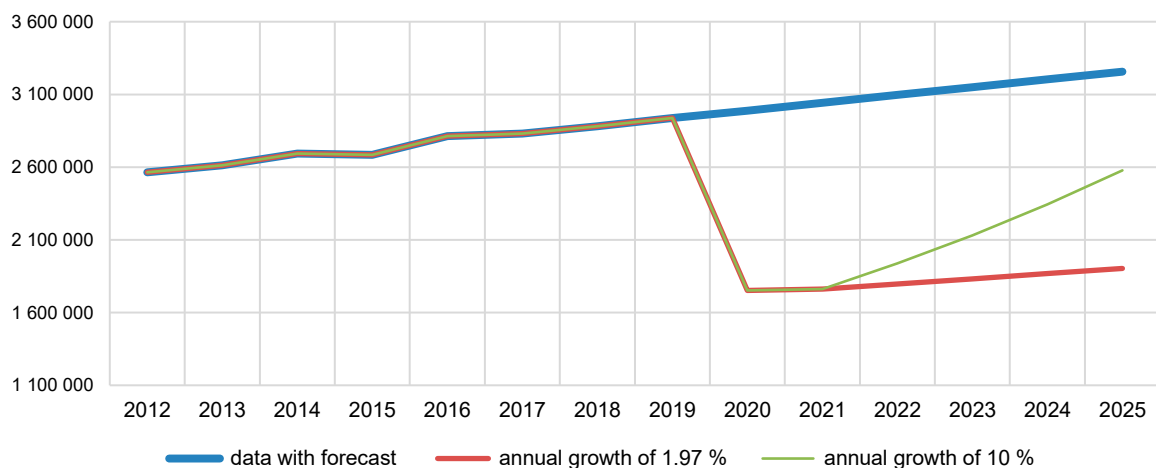


Figure 4. Forecasts for Germany (own compilation based on Eurostat data)

year to year, the number of passengers traveling by rail will not reach pre-pandemic levels by 2025.

Figure 5 shows the forecasts for Spain. The first forecast was built based on a linear trend ( $y_t = 9005.6242t + 543791.6667$ ,  $R^2 = 0.8680$ ,  $V_S = 1.90\%$ ). The other assumes an annual increase of 1.61% in the number of passengers. Again,

the differences between the received forecast results are clearly visible. If the increase in the number of passengers remains at the same level as before the pandemic (1.61%) or increases by 10% from year to year, the number of passengers traveling by rail will not reach pre-pandemic levels by 2025.

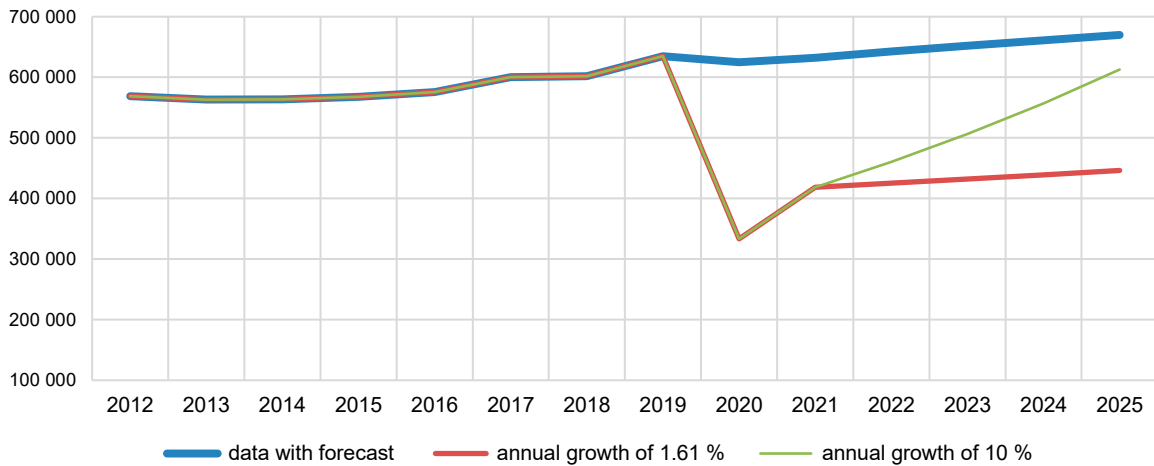


Figure 5. Forecasts for Spain (own compilation based on Eurostat data)

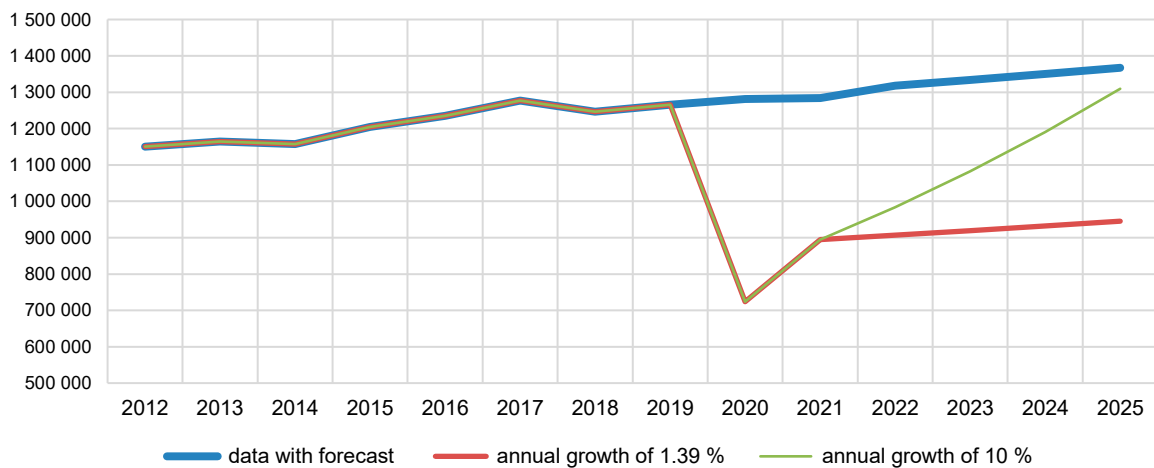


Figure 6. Forecasts for France (own compilation based on Eurostat data)

Figure 6 shows the forecasts for France. The first forecast was built based on a linear trend ( $y_t = 16534.8364t + 1135732.4000$ ,  $R^2 = 0.8762$ ,  $V_S = 1.63\%$ ). The other assumes an annual increase of 1.39% in the number of passengers. Again, the differences between the received forecast results are clearly visible. If passenger growth remains at the same level as before the pandemic (1.39%) or the number of passengers grows by 10% from year to year, the number of passengers traveling by rail will not reach pre-pandemic levels by 2025.

Figure 7 shows the forecasts for Italy. The first forecast was built based on a linear trend ( $y_t = 3716.2848t + 851733.1333$ ,  $R^2 = 0.6747$ ,  $V_S = 0.95\%$ ). The other assumes an annual increase of 0.72% in the number of passengers. Again, the differences between the received forecast results are clearly visible. If passenger growth remains at the same level as before the pandemic (0.72%) or the number of passengers grows by 10% from year to year, the number of passengers traveling by rail will not reach pre-pandemic levels by 2025.

Figure 8 shows the forecasts for Sweden. The first forecast was built based on a linear trend ( $y_t = 9933.7515t + 177870.0667$ ,  $R^2 = 0.9750$ ,  $V_S = 2.19\%$ ). The other assumes an annual increase of 4.61% in the number of passengers. Again, the differences between the received forecast results are clearly visible. If passenger growth remains at the same level as before the pandemic (4.61%) or the number of passengers grows by 10% from year to year, the number of passengers traveling by rail will not reach pre-pandemic levels by 2025.

Figure 9 shows the forecasts for Switzerland. The first forecast was built based on a parabolic trend ( $y_t = -3688.6061t^2 + 45932.0485t + 465672.0667$ ,  $R^2 = 0.7303$ ,  $V_S = 47.71\%$ ) and indicates a declining trend. The second assumes an annual increase of 3.10% in the number of passengers. Assuming that, before the pandemic, the number of passengers carried was around 600,000, an increase of 3.10% will not allow a return to pre-pandemic levels. If the number of passengers grows by 10% year after year, this level will be reached in 2025.



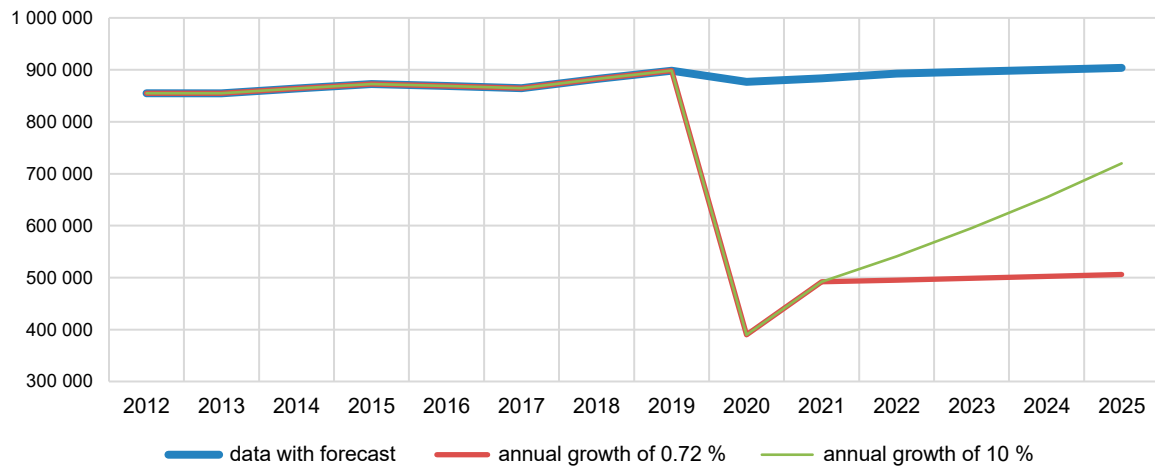


Figure 7. Forecasts for Italy (own compilation based on Eurostat data)

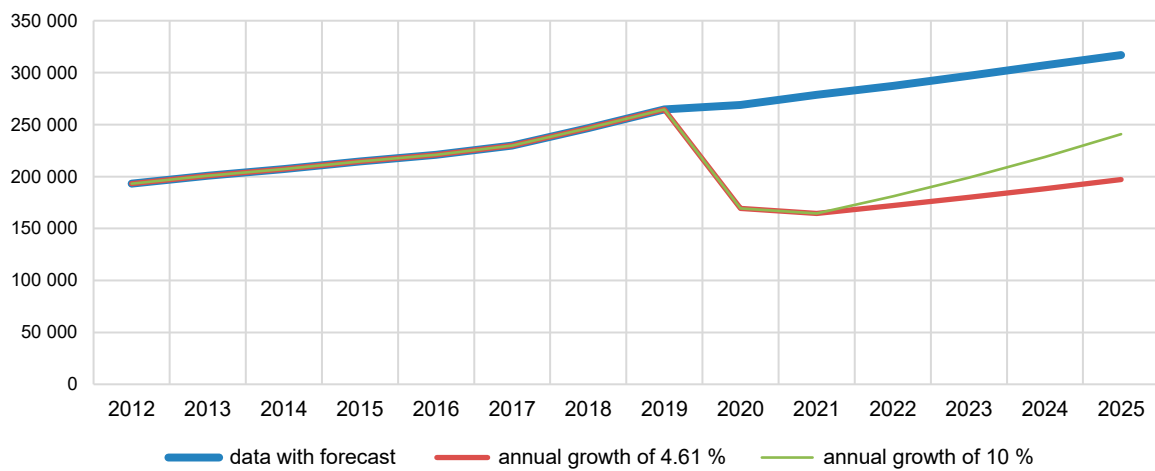


Figure 8. Forecasts for Sweden (own compilation based on Eurostat data)

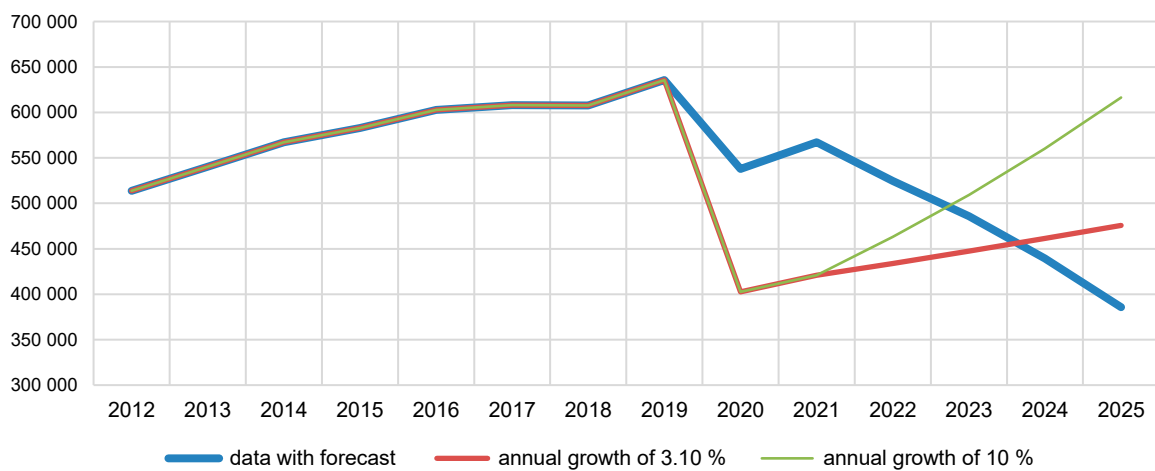


Figure 9. Forecasts for Switzerland (own compilation based on Eurostat data)

### Discussion – Traffic behavior during COVID-19 and its potential implications for rail transport

Transportation behavior defines an individual's approach to traveling by different modes and

for different purposes; it includes the relationship between the decisions made and socio-demographic and spatial factors. They can be defined both as the number of trips and the length of space actually traveled, as well as the frequency and type of means of transportation used (Schellhase, 2000). It is also

a complex of activities and actions aimed at satisfying transportation needs. Traffic behavior includes the totality of decisions on how to move, as well as the very process of traversing space (Szołtysek, 2011). Zemlin (2005) describes them as the type of means of communication used by an individual. Communication behavior is also a complex of activities and actions aimed at satisfying transportation needs. According to Szołtysek (2011), communication behavior includes the totality of decisions on ways to move, as well as the process of crossing space itself. Without movement, individuals would not have the opportunity to fulfill many of their needs, such as those related to maintaining or improving their quality of life, leisure, or socializing.

The emergence of the pandemic triggered an avalanche of drastic measures to curb its spread. Overnight, the circumstances necessitated radical changes in the daily life of the population (Loxton et al., 2020). Three basic aspects of life have undergone the greatest changes: (1) activity patterns, (2) ways of working and studying, and (3) modes and conditions of movement. From the point of view of rail operators' transportation policies, it is particularly important to seek answers to the question of how the external determinants of mobility during the pandemic will affect long-term and structural changes in mobility behavior. These are determined by such factors as transit characteristics, socio-psychological characteristics, the individual's accessibility to individual automobile transportation, and the characteristics of the mode of transport (more information is provided in an earlier paper (Kauf & Tłuczak, 2013)). Undoubtedly, preferences and habits also play an essential role (Schönfelder & Axhausen, 2010). The latter make decisions about our mode of transportation routine and make us reluctant to change our habits. Nevertheless, there are turning points in everyone's life that prompt us to change our modes of transportation (Müggenburg, Busch-Geertsema & Lanzendorf, 2015). In the literature, they are referred to as windows of opportunity (Schäfer, Jaeger-Erben & Bamberg, 2012). These occasions include events related to the following (Müggenburg, Busch-Geertsema & Lanzendorf, 2015):

- (1) career (starting a career after college, career advancement, job change, retirement, etc.) and personal development (starting a household, birth of a child, child leaving home, new hobby, etc.);
- (2) adaptability of long-term decisions, which may be caused by or may lead to preceding life events

- (e.g., car payments, season tickets, driver's license, etc.);
- (3) exogenous factors (new information, infrastructure, company car, etc.);
- (4) long-term, unobservable processes that are not treated as breakthrough events (aging process, cohort effect, socialization, etc.).

The indicated changes in people's lives can lead to modifications in travel patterns, as well as activity patterns (Hilgert et al., 2018). It can be considered that the events associated with the pandemic had the character of such a watershed event, which changed the communication behavior of the population in the long term. The pandemic should be classified as an exogenous factor with a community-wide impact. Everyone knows that changing habits without external coercion is difficult, and the time required to form new habits depends on the type of new behavior and the inconvenience associated with its introduction – it is definitely easier to form habits of simple activities (such as eating fruit for breakfast) than those that require more effort (such as daily sports training) (Dean, 2013). Besides, acceptance of change is easier when there are positive experiences, i.e., we will accept cycling more easily when we have positive experiences from moving together earlier in life (e.g., cycling trips with parents) (Sigurdardottir et al., 2013; Strömberg & Karlsson, 2016). In addition, it can be assumed that new experiences help form new habits if these habits help reduce prejudice (e.g., cycling requires a lot of effort). The pandemic situation was associated with restrictions on movement, and the need to maintain social distance undoubtedly constituted a new experience. As a result of these factors, people changed their behavior, and the long duration of the pandemic solidified these behaviors, and new habits were formed. These new experiences, forced by the exogenous factors associated with COVID-19 affecting people's attitudes, are defined as “a relatively constant tendency for a person to position himself positively or negatively toward a given object” (Strelau, 2000). A favorable attitude is a condition for choosing a certain object (in our case, a means of communication).

This issue is of particular interest in the context of the future of rail transport, which to this day has not “rebuilt” the number of passengers from the pre-pandemic period. Since the second quarter of 2020, we have seen a systematic decline in the number of passengers transported by rail, which was caused by the pan-European lockdown. In the first quarter of 2021, in the so-called

second wave of the pandemic, further restrictions on the movement of people were introduced in many countries, resulting in a further decline in rail passengers. As the forecast results presented here show, even assuming a 10 % annual increase in passenger numbers, even by 2025, most European countries will not reach pre-pandemic levels. Before the outbreak, it was estimated that passenger transport was expected to grow by 42 % by 2050 (European Commission, 2019).

To summarize, the pandemic has structurally affected the transportation behavior and mode choice of residents. Trends are, therefore, negative, and rail operators must take intensified measures to make their offerings more attractive and attract passengers.

### **Towards rail as the transport of the future – Summary and conclusions**

External global shocks tend to raise safety and health concerns in mass transportation. At the same time, they cause changes in mobility behavior, reducing demand for mass transportation. This finding was confirmed in the presented results of a study of the impact of the COVID-19 pandemic on the volume of rail passenger transport. The results are not optimistic and highlight the scale of the problems currently facing rail transport operators. The presented dynamics of passenger growth until 2025 display that measures need to be taken by rail operators to increase the demand for transportation in the long term, support sustainable development, and even become the transportation of the future. Making the railroads of the future more attractive requires not only adapting the European rail sector to new challenges but, above all, reconsidering the role that passenger rail transport can play in the future. In this context, it seems reasonable to learn the lessons of the pandemic period and develop a new mobility paradigm that will help insulate railroads from the consequences of further health crises. Rail passenger transport has a chance to be:

(1) More resilient (responsive) – the composition of passenger cars allows for quick and efficient adjustment of seating arrangements to meet the needs that arise. Railroads can provide safe, independent compartments designed for a small number of passengers to maintain the desired social distance. Automated sanitary controls, such as thermal imaging cameras, electronic ticketing systems, and train passenger tracking applications, can be implemented at stations and

at platform and carriage entrances, which can facilitate the collection of data on people who might come into contact with an infected person. Also of note is the ease of disinfecting train cars between train runs.

(2) Sustainable and environmental – environmental protection measures are not just a temporary trend, but a development strategy to grow faster and build a stable position for the railroad in the long term. In this context, it is necessary to invest in modern, low-emission rolling stock (i.e., multi-system locomotives and hybrid rolling stock) and environmentally friendly stopping stations, which will translate into lower greenhouse gas emissions.

At this point, it is worth pointing out that the aforementioned European Green Deal promoting sustainability is a document developed before the pandemic, and this creates the need to reform mobility policy and its implications for the rail transport sector to ensure the implementation of best practices in a fragile health and financial situation (current inflation).

Despite the negative effects that the COVID-19 pandemic has had on the rail transport sector, it can be considered that the current situation can be viewed as an opportunity to improve the competitive position of railroads and position them as the transportation of the future. In order for this to happen, however, the railroad faces a vast number of challenges, including promoting sustainable transportation while initiating changes in the population's transportation behavior. The result of these activities should be a shift from individual car transportation to rail transportation, which can be more resilient and is the most environmentally friendly of all modes of transportation. Railroads have the potential to guarantee the mobility of residents while ensuring social distance and health security. Creating preferences toward rail transportation is not an easy task and should be implemented in multiple stages. In the short term, railroads should strive to restore passenger numbers to pre-pandemic levels, such as by eliminating existing inconveniences (e.g., delays) of travel and increasing the reliability and safety of travel. In the medium term, passenger transport managers and government institutions should make every effort to attract new customers in addition to recovered passengers. Achieving this goal, however, requires knowledge of where, when, and how often people travel.

Focusing on new patterns of mobility behavior, rail operators should strive to make travel more

flexible, convenient, and cost-effective. Rail carriers should adjust both schedules and prices to meet the needs of travelers. In Germany, for example, DB, in an effort to boost rail travel, introduced a monthly ticket for regional railroads in 2022 at a price of just €9. As of May 01, 2023, a ticket for all journeys within the country at a price of €49 is to come into effect. In the long term, it is necessary to strive for the development of rail infrastructure and the modernization and digitalization of railroads, so that they can become a viable alternative to individual car transport. Only then will it be possible to achieve sustainable development goals aimed at reducing automobile mobility. This entails expanding the density of the rail network and the high-speed rail. High-speed connections are a key factor for success, as travel time has a decisive impact on rail's share of total transportation compared to air transport. However, these measures require significant capital investment. Upgrading the rolling stock to make it more comfortable and traveler-friendly is also not insignificant. The key to success, however, is changing the transportation behavior of residents through communication, building awareness toward rail transportation services, and fostering a desire to travel by rail.

To summarize, rail operators have opportunities to restore passenger rail to pre-pandemic COVID-19 levels and increase their share of freight. Focusing on restoring and expanding the passenger base, promoting rail travel, and expanding rail service offerings can provide a real opportunity for rail operators to achieve market success and make rail the mobility mode of the future.

## References

- AHMAD, M., FRANZ, F., NAUCLÉR, T. & RIEFER, D. (2022) *Opportunities for industry leaders as new travelers take to the skies*. [Online] April 5. Available from: <https://www.mckinsey.com/industries/travel-logistics-and-infrastructure/our-insights/opportunities-for-industry-leaders-as-new-travelers-take-to-the-skies> [Accessed: February 23, 2023].
- BARCZAK, A. (2015) Measurement of seasonal fluctuations in passenger traffic using the case study of Gdańsk airport. *Folia Pomeranae Universitatis Technologiae Stetinensis, Oeconomica* 321(80)3, pp. 5–14, (in Polish).
- BARCZAK, A. (2016) Metoda trendów jednoimiennych okresów jako narzędzie prognozowania ruchu pasażerskiego na przykładzie Portu Lotniczego Gdańsk. In: Feliks, J. (Ed.) *Wybrane Zagadnienia Logistyki Stosowanej* 4, pp. 13–23, Cracow, Poland: AGH University of Science and Technology Publisher.
- BARCZAK, A. (2021) COVID-19 pandemic – financial consequences for Polish airports – selected aspects. *Aerospace* 8 (11), 353, doi: 10.3390/aerospace8110353.
- BARCZAK, A., DEMBIŃSKA, I., ROZMUS, D. & SZOPIK-DEPCZYŃSKA, K. (2022) The impact of COVID-19 pandemic on air transport passenger markets-implications for selected EU airports based on time series models analysis. *Sustainability* 14, 4345, doi: 10.3390/su14074345.
- BILLAH, B., KING, M.L., SNYDER, R. & KOEHLER, A.B. (2006) Exponential smoothing model selection for forecasting. *International Journal of Forecasting* 22 (2), pp. 239–247, doi: 10.1016/j.ijforecast.2005.08.002.
- BROWN, R.G. & MEYER, R.F. (1961) The fundamental theorem of exponential smoothing. *Operations Research* 9 (5), pp. 603–767, doi: 10.1287/opre.9.5.673.
- CHAPUIS, R., DELPORTE, T. & LOTZ, C. (2021) *Boosting passenger preference for rail*. Report. Available from: <https://www.mckinsey.com/industries/travel-logistics-and-infrastructure/our-insights/boosting-passenger-preference-for-rail> [Accessed: February 23, 2023].
- DEAN, J. (2013) *Making Habits, Breaking Habits: How to Make Changes that Stick*. Boston: Da Capo Press.
- European Commission (2019) *Transport in the European Union. Current Trends and Issues*. Available from: [https://transport.ec.europa.eu/news-events/news/transport-european-union-current-trends-and-issues-2019-03-13\\_en](https://transport.ec.europa.eu/news-events/news/transport-european-union-current-trends-and-issues-2019-03-13_en) [Accessed: February 20, 2023].
- Eurostat (2023) *Passenger transport by type of transport (detailed reporting only)*. [Online]. Available from: [https://ec.europa.eu/eurostat/databrowser/view/rail\\_pa\\_typedpas/default/map?lang=en](https://ec.europa.eu/eurostat/databrowser/view/rail_pa_typedpas/default/map?lang=en) [Accessed: February 23, 2023].
- HILGERT, T., VON BEHREN, S., EISENMANN, C. & VORTISCH, P. (2018) Are activity patterns stable or variable? Analysis of three-year panel data. *Transportation Research Record. Journal of the Transportation Research Board* 2672 (47), doi: 10.1177/0361198118773557.
- KAUF, S. & TLUCZAK, A. (2013) *Metody i techniki badań marketingowych na przykładzie zachowań komunikacyjnych opolan*. Opole, Poland: Wydawnictwo Uniwersytetu Opolskiego.
- KOVAČEVIĆ, S., REBIĆ, M. & KURUŠIĆ, D. (2021) The Impact of the COVID-19 Pandemic on the Labor Market of Bosnia and Herzegovina: Application of the Exponential Equalization Methods. *Proceedings of the 8th REDETE Conference Researching Economic Development and Entrepreneurship in Transition Economies*, Banja Luka, September 03–05, 2021, pp. 106–129.
- LOXTON, M., TRUSKETT, R., SCARF, B., SINDONE, L., BALDRY, G. & ZHAO, Y. (2020) Consumer behaviour during crises: Preliminary research on how coronavirus has manifested consumer panic buying, herd mentality, changing discretionary spending and the role of the media in influencing behaviour. *Journal of Risk and Financial Management* 13 (8), 166, doi: 1911-8074/13/8/166.
- MANCUSO, A.C.B. & WERNER, L. (2013) Review of combining forecasts approaches. *Independent Journal of Management & Production* 4 (1), pp. 248–277, doi: 10.14807/ijmp.v4i1.59.
- MONTGOMERY, D.C., JOHNSON, L.A. & GARDINER, J.S. (1990) *Forecasting and Time Series Analysis*. 2<sup>nd</sup> Edition. McGraw-Hill.
- MÜGGENBURG, H., BUSCH-GEERTSEMA, A. & LANZENDORF, M. (2015) Mobility biographies: A review of achievements and challenges of the mobility biographies approach and a framework for further research. *Journal of Transport Geography* 46, pp. 151–163, doi: 10.1016/j.jtrangeo.2015.06.004.

19. ORAL, İ.O. (2019) Comparison of the winters' seasonality exponential smoothing method with the pegels' classification: Forecasting of Turkey's economic growth rates. *Anadolu Üniversitesi Sosyal Bilimler Dergisi* 19 (3), pp. 275–294, doi: 10.18037/ausbd.632023.
20. OSTERTAGOVA, E. & OSTERTAG, O. (2011) The Simple Exponential Smoothing Model. *Proceedings of the 4th International Conference: Modelling of Mechanical and Mechatronic Systems 2011*, September 20–22, 2011, Herľany, Slovak Republic, pp. 380–384.
21. OSTERTAGOVA, E. & OSTERTAG, O. (2012) Forecasting using simple exponential smoothing method. *Acta Electrotechnica et Informatica* 12 (3), pp. 62–66, doi: 10.2478/v10198-012-0034-2.
22. PERZYŃSKA, J. (2017) Combined forecasts in testing of econometric models encompassing – empirical example. *Folia Pomeranae Universitatis Technologiae Stetinensis, Oeconomica* 337(88)3, pp. 47–56, doi: 10.21005/oe.2017.88.3.05 (in Polish).
23. SCHÄFER, M., JAEGER-ERBEN, M. & BAMBERG, S. (2012) Life events as windows of opportunity for changing towards sustainable consumption patterns? *Journal of Consumer Policy* 35 (1), pp. 65–84, doi: 10.1007/s10603-011-9181-6.
24. SCHELLHASE, R. (2000) *Mobilitätsverhalten im Stadtverkehr. Eine empirische Untersuchung zur Akzeptanz verkehrspolitischer Maßnahmen*. Wiesbaden: Deutscher Universitätsverlag.
25. SCHÖNFELDER, S. & AXHAUSEN, K.W. (2010) *Urban rhythms and travel behaviour: spatial and temporal phenomena of daily travel*. Ashgate Publishing.
26. SIGURDARDOTTIR, S.B., KAPLAN, S., MÖLLER, M. & TEASDALE, T.W. (2013) Understanding adolescents' intentions to commute by car or bicycle as adults. *Transportation Research Part D: Transport and Environment* 24, pp. 1–9, doi: 10.1016/j.trd.2013.04.008.
27. STRELAU, J. (2000) *Psychologia. Podręcznik akademicki*. Gdańsk, Poland: Gdańskie Wydawnictwo Psychologiczne.
28. STRÖMBERG, H. & KARLSSON, I.M. (2016) Enhancing utilitarian cycling: A case study. *Transportation Research Procedia* 14, pp. 2352–2361, doi: 10.1016/j.trpro.2016.05.264.
29. SZOŁTYSEK, J. (2011) *Kreowanie mobilności mieszkańców miast*. Warszawa, Poland: Wolters Kluwer.
30. WINKLER, R.L. & MAKRIDAKIS, S. (1983) The combination of forecasts. *Journal of the Royal Statistical Society Series A (General)* 146 (2), pp. 150–157, doi: 10.2307/2982011.
31. ZEMLIN, B. (2005) *Das Entscheidungsverhalten bei der Verkehrsmittelwahl*. EUL Verlag.

**Cite as:** Barczak, A., Kauf, S. (2024) Traffic behavior during the COVID-19 pandemic and its potential consequences for passenger rail transport in the example of selected European countries. *Scientific Journals of the Maritime University of Szczecin, Zeszyty Naukowe Politechniki Morskiej w Szczecinie* 78 (150), 22–34.



© 2024 Author(s). This is open access article licensed under the Creative Commons Attribution (CC BY) License (<https://creativecommons.org/licenses/by/4.0/>).