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Modeling the dynamics of changes in CO_2 emissions from Polish road transport in the context of COVID-19 and decarbonization requirements

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Emissions from transport account for 20–25% of anthropogenic global carbon dioxide emissions [17, 37], with more than 70% coming from road transport, making it an extremely important topic in the context of decarbonization. The aim of the article is to analyze the trend of CO_2 generated from road transport, taking into account various sources, and also to examine how reduced mobility during the pandemic affected the emissions at the time. For this purpose, a time series containing observations up to the pandemic outbreak and a time series containing additional observations from the pandemic period were analyzed. For each time series, a trend was determined and described by a polynomial and then verified to see if the pandemic phenomenon significantly affects a parameter of the proposed model, using appropriate statistical tests.

Key words: *transport decarbonization, CO_2 emissions, road transport, COVID-19 pandemic, polynomial model*

1. Introduction

Global warming, the main cause of which is the growing emission of carbon dioxide, causes drastic consequences for many ecosystems, bringing about irreversible changes in them [27, 36, 38]. The use of petroleum fuels in transport determines its significant share in greenhouse gas emissions, which is why this sector faces the greatest demands [5, 12, 23]. Meanwhile, the progressing globalization, population growth, increasing demand for goods, as well as the dynamic development of the tourism industry and the number of people travelling do not make this task easier, especially since it is estimated that by the 2050, the EU economy will more than double [10].

Emissions from transport account for 20–25% of anthropogenic global carbon dioxide emissions [17, 37], of which 71.7% are from road transport, but taking into account the production of cars and the construction of road infrastructure, this number increases to 37% of all emissions [7, 14, 16, 24]. Transport uses 30% of the world' energy. Although only 7% of the population owns cars, this translates into 40% of the world's petrol production.

Cars are considered the most polluting means of transport and at the same time the most unsafe [3, 4, 18]. They are also the largest emitter of toxic chemical compounds not subject to legal regulation, such as butadiene, benzene and others [22, 25]. The area necessary to build a road (30 to 40 m on average) is much larger than the requirements for railway traction (10 to 14 m) [25]. What's more, 30% of car journeys in the European Union do not exceed 3 km, and 50% – 6 km [39], so they could be successfully replaced by environmentally friendly natural forms of transport, such as bicycles.

The share of Polish road transport in the total emissions of the European Union is significant. Poland has been occupying leading positions for years [9]. Moreover, due to the intensive increase in passenger and transport activity, CO_2 emissions are constantly growing, increasing in 2020 by almost 150% compared to 2000, while emissions throughout the EU remain relatively constant [2].

The transport sector is therefore a challenge on the way to achieving climate neutrality, related to the reduction of greenhouse gases emissions, which is the result of the European climate policy. Currently, the European Parliament requires a 40% reduction in greenhouse gas emissions by EU countries by the 2030, compared to the level of 2005 [29]. This is a recent change (March 2023). The previous target was 30%.

Therefore, the article analyses the current dynamics of changes in CO_2 emissions from road transport, including various types of transport means. Mathematical identification of the examined time series and determination of the forecast was aimed at relating the current level of CO_2 emissions to the requirements imposed by the EU in this regard.

In addition, the article features an analysis of the impact of the COVID-19 pandemic on CO_2 emissions. Global movement restrictions, limited travel options and remote work, as well as fear of contagion, have strongly influenced changes in people's preferences in their choice of transport and travel in general. More people staying indoors or using safer forms of transport like cycling or walking may have reduced these emissions, as confirmed by studies by a number of authors [11, 13, 20, 32, 42]. On the other hand, the fear of coming into contact with an infected person has fostered a switch from public to private transport [1,6], and a number of authors believe that the decrease in emissions was too short-lived to have a relative effect [31, 33]. Therefore, the article also features an attempt to answer the question of how the COVID-19 pandemic in Poland affected the trend in CO_2 emissions, taking into account different modes of transport.

For this purpose, time series of CO_2 emissions from transport, published by the European Environment Agency, expressed in Gg [8], were analyzed. Time series with observations up to the outbreak of the pandemic and time series with additional observations from the pandemic period were analyzed.

For each time series, a trend was determined and described by a polynomial and then verified to see if the pandemic phenomenon significantly affects a parameter of the proposed model, using appropriate statistical tests. A detailed survey procedure is presented in Chapter 2. The lack of confirmation of the significance of the impact of the pandemic on the model coefficients means that the hazard did not significantly affect CO_2 emissions.

2. Materials and methods

2.1. Determining the trend in a time series

The trend in the time series $\{x_{t_i}\}_{1\le i\le n}$ is identified as a polynomial [15, 41]

$$x_{\tau_i} = \beta_0 + \beta_1\tau_i + \cdots + \beta_k\tau_i^k + \varepsilon_{\tau_i} \tag{1}$$

where $\{\varepsilon_i\}_{1\le i\le n}$ is a sequence of independent random variables with a normal distribution $N(0,\sigma^2)$ and $x_{\tau_i} \overset{\text{def}}{=} x_{t_i}$. The trend occurring in the series is identified using a k degree polynomial. The dependence (1) between the endogenous variable and the predictors (transformations of the variable τ) is linear. At the beginning we define objects:

$$X = \begin{bmatrix} 1 & \tau_1 & \dots & \tau_1^k \\ 1 & \tau_2 & \dots & \tau_2^k \\ \vdots & \vdots & & \vdots \\ 1 & \tau_n & \dots & \tau_n^k \end{bmatrix}, \quad Y = \begin{bmatrix} x_{\tau_1} \\ x_{\tau_2} \\ \vdots \\ x_{\tau_n} \end{bmatrix},$$

$$\varepsilon = \begin{bmatrix} \varepsilon_0 \\ \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{bmatrix}, \quad \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix}$$

therefore, the dependence (1) can be presented in linear form [21,24]:

$$Y = X\beta + \varepsilon \tag{2}$$

Using the Least Squares Method (LSM) [41] the values of the model parameters can be estimated using the formula

$$\hat{\beta} = (X^TX)^{-1}X^TY \tag{3}$$

The vector of residuals $\varepsilon \in \mathbb{R}^n$ can be presented as $\varepsilon = Y - X\hat{\beta}$. Coefficient of determination [41] is determined as follows

$$R^2 = 1 - \frac{\sum_{j=1}^n \varepsilon_j^2}{\sum_{j=1}^n \left(x_{\tau_i} - \bar{x}\right)^2}, \tag{4}$$

where $\bar{x} = \frac{1}{n}\sum_{j=1}^n x_{\tau_i}$ and the estimator of the variance of the residuals is equal

$$\hat{\sigma}^2 = \frac{1}{n-k-1}\sum_{j=1}^n \varepsilon_j^2$$

Values of variance of structural parameters [41] are determined as follows

$$S^2 = (S_0^2, S_1^2, \dots, S_k^2) = \mathrm{diag}(\hat{\sigma}^2(X^TX)^{-1}).$$

Thus, each of the structural parameters β_j has a normal distribution $N(\hat{\beta}_j, S_j^2)$ for $0 \le j \le k$. For each parameter β_j the significance of the influence of component τ_i^j on the realizations of the series according to model (1) is tested. At the significance level $0 < \alpha < 1$ for each structural parameter β_j we create a null hypothesis

H_0: $\beta_j = 0$

against an alternative hypothesis

H_0: $\beta_j \ne 0$.

The test statistic

$$t = \frac{\hat{\beta}_j}{\sqrt{S_j^2}} \tag{5}$$

has t – distribution with $n-k-1$ degrees of freedom [15,34,40]. The test probability is equal:

$$p.\mathrm{val}_j = 2\big(1 - \Psi(|t|)\big)$$

where $\Psi(\cdot)$ is t – distribution function with $n-k-1$ degrees of freedom. If $p.\mathrm{val}_j < \alpha$ then for the parameter β_j the null hypothesis H_0 is rejected in favor of the alternative hypothesis H_1. Therefore, the component τ_i^j significantly affects the realization of the time series defined by formula (1).

The key in the analyzed mathematical equation is the choice of the degree of the polynomial. To select the appropriate polynomial, the Ramsey RESET test (linearity test) [21, 28] was used in the research. The degree of the polynomial is chosen as the lowest natural number for which the coefficient of determination is at a sufficiently high level and there are no grounds to reject the null hypothesis for the linearity test.

2.2. Study of the impact of COVID-19 on CO_2 emissions

First, a time series of CO_2 emissions is considered for pre-pandemic data, i.e., data covering the years up to and including 2019. Thus, for the series $\{x_{\tau_i}\}_{1\le i\le n-1}$ the model (1) is identified and, taking into account the linearity test of the models, the degree of the polynomial $k \in \mathbb{N}$ is determined. Using LSM the structural parameters of the model and the variances of these structural parameters are determined, therefore $\beta_i^{2019} \sim N\big(\hat{\beta}_i^{2019}, S_i^{2019}\big)$ for $0 \le i \le k$.

Next, the time series of CO_2 emissions for data that includes the COVID-19 pandemic are analyzed, i.e., for data including the year 2020. Thus, for the series $\{x_{\tau_i}\}_{1\le i\le n}$ the model (1) for the degree of the polynomial $k \in \mathbb{N}$ is identified. Using LSM the structural parameters of the model and the variances of these structural parameters are determined, therefore $\beta_i^{2020} \sim N\big(\hat{\beta}_i^{2020}, S_i^{2020}\big)$ for $0 \le i \le k$.

In the next step, for each j indices, $0 \le j \le k$ at significance level $\alpha = 0.05$ the null hypothesis is created:

H_0: $\beta_j^{2019} = \beta_j^{2020}$ (no impact of pandemic on parameter β_j)

against an alternative hypothesis:

H_1: $\beta_j^{2019} \ne \beta_j^{2020}$ (significant impact of pandemic on parameter β_j)

The test statistic

$$T = \frac{\hat{\beta}_j^{2019} - \hat{\beta}_j^{2020}}{\sqrt{\frac{S_j^{2019}}{n-k-2} + \frac{S_j^{2020}}{n-k-1}}} \tag{6}$$

has a normal distribution $N(0,1)$ [15, 41]. The test probability is equal:

$$p.\mathrm{val}_j = 2\big(1 - \Phi(|T|)\big)$$

where $\Phi(\cdot)$ denotes the standard normal distribution $N(0,1)$. If $p.\text{val}_j < \alpha$ then the null hypothesis H_0 is rejected in favor of H_1.

If there is such j index, $1 \le k$ for which $p.\text{val}_j < \alpha$, it is considered that the estimator of β_j parameter determined from observations up to the pandemic and observations with the onset of the pandemic are significantly different, and therefore the pandemic had a significant impact on the trend of CO_2 emissions. If for each j indices, $1 \le k$ the condition $p.\text{val}_j \ge \alpha$ is satisfied, then for each structural parameter, the estimators obtained from observations up to the pandemic and observations with the start of the pandemic are not significantly different from each other, therefore the pandemic did not have a significant impact on CO_2 emissions.

3. Evaluation of the trend of CO_2 emissions in road transport

3.1. Road transport

First, CO_2 emissions from road transport as a whole were evaluated without breaking them down by mode of transport. Figure 1 presents the time series under study (black curve).

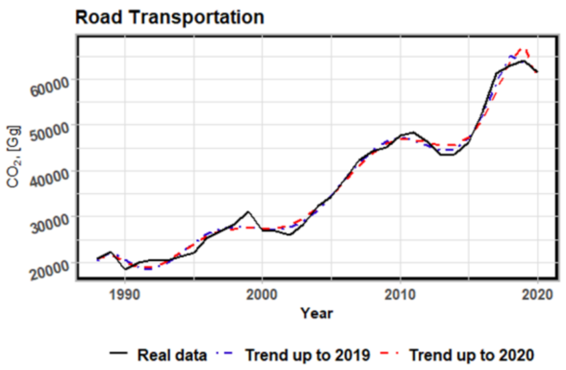

Fig. 1. CO_2 Emission for Road Transportation [8]

Then, for the time series presented, a model built only for the pre-pandemic period was proposed (blue line in Fig. 1). The estimators of structural parameters, standard deviations, t-statistic values and p-values are presented in Table 1.

Table 1. Structural parameters, standard errors, values of t-statistic and p-values for the trend to the pre-pandemic period

	Estimate	Std. error	t value	p-value
β_0	7115.71935	5166.94560	1.37716	0.18172
β_1	22985.07637	6162.91969	3.72958	0.00110
β_2	–12041.9597	2495.18762	–4.82607	0.00007
β_3	2769.26980	479.62213	5.77386	0.00001
β_4	–327.12113	50.15569	–6.52211	< 1e–5
β_5	21.43286	3.01362	7.11200	< 1e–5
β_6	–0.78550	0.10381	–7.56667	< 1e–5
β_7	0.01505	0.00190	7.90711	<1e–5
β_8	–0.00012	0.00001	–8.15249	<1e–5

The coefficient of determination is equal to 0.9907, and the standard deviation of the residuals is equal to 1524.28. At the significance level $\alpha = 0.05$, the H_0 hypothesis was rejected in favor of H_1 for the structural parameters of $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8$, therefore the predictors of these parameters significantly affect the polynomial trend in the time series. The value of the statistic for the Ramsey RESET test is 1.6778, while the p-value is 0.2496.

In the next step, a model was built for data covering the period of the pandemic (red line in Fig. 1). Table 2 presents the estimators of structural parameters, standard deviations, values of t-statistics and p-values for the entire period.

Table 2. Structural parameters, standard errors, values of t-statistic and p-value for the trend to the entire period

	Estimate	Std. error	t value	p-value
β_0	12173.08505	5969.19873	2.03932	0.05258
β_1	15486.44602	6946.95856	2.22924	0.03542
β_2	–8500.03179	2739.16084	–3.10315	0.00485
β_3	2003.84146	512.08133	3.91313	0.00066
β_4	–239.32353	52.03960	–4.59887	0.00012
β_5	15.74571	3.03706	5.18452	0.00003
β_6	–0.57695	0.10158	–5.67979	0.00001
β_7	0.01102	0.00181	6.09446	< 1e–5
β_8	–0.00009	0.00001	–6.43854	< 1e–5

The coefficient of determination is equally high at 0.9873. The standard deviation of the residuals is equal to 1836.77. At the significance level $\alpha = 0.05$, the hypothesis H_0 was rejected in favor of H_1 for the parameters $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8$. Thus, predictors at these parameters significantly affect the polynomial trend in the time series.

For the polynomials constructed above, their parameters were compared. Table 3 presents the calculated values of statistics (6) and p-values for the test of differences of structural parameters.

Table 3. T-statistic values and p-value for the tests of differences in structural parameters

	T	p-value
β_0	–3.10942	0.00187
β_1	3.91841	0.00009
β_2	–4.63753	< 1e–5
β_3	5.29107	< 1e–5
β_4	–5.88978	< 1e–5
β_5	6.44278	< 1e–5
β_6	–6.95724	< 1e–5
β_7	7.43869	< 1e–5
β_8	–7.89137	< 1e–5

At the significance level $\alpha = 0.05$, the H_0 hypothesis was rejected in favor of H_1 for all structural parameters. Thus, the parameters are significantly different for the polynomial trend determined for the CO_2 emission series up to the time of the pandemic outbreak and the polynomial trend determined for the CO_2 emission series containing the first year of the pandemic. Thus, the COVID-19 pandemic significantly affected the CO_2 emissions trend analyzed for road transport in Poland, as a whole.

In the next stage of the study, an analogous analysis was made, however, taking into account the different modes of transport. Passenger cars, light duty trucks, heavy duty trucks and motorcycles were studied.

3.2. Passenger cars

Passenger cars make up the majority of the vehicle market in Poland (more than 60% of the market). The latest available data shows that at the end of 2022, 26.675 million passenger cars were registered in the database of the Central Register of Vehicles and Drivers (CEPiK), 577,000 more than a year earlier [35]. In Fig. 2 CO_2 emissions (black line) are also on an upward trend.

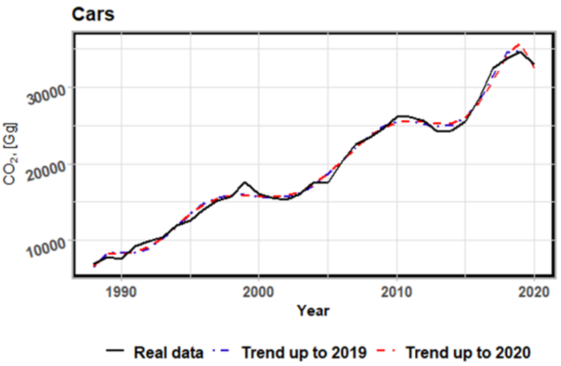

Fig. 2. CO_2 emissions for cars [8]

According to the adopted algorithm, the model was first built for the pre-pandemic period only (blue line in Fig. 2). Its structural parameters, standard deviations, t-statistic values and p-values are presented in Table 4.

Table 4. Structural parameters, standard errors, values of t-statistic and p-value for the trend to the pre-pandemic period

	Estimate	Std. error	t value	p-value
β_0	–902.69310	2570.25660	–0.35121	0.72863
β_1	12031.29715	3065.69611	3.92449	0.00068
β_2	–5793.93596	1241.21153	–4.66797	0.00011
β_3	1326.84643	238.58427	5.56133	0.00001
β_4	–156.72823	24.94956	–6.28180	< 1e–5
β_5	10.23508	1.49910	6.82748	< 1e–5
β_6	–0.37295	0.05164	–7.22225	< 1e–5
β_7	0.00710	0.00095	7.49445	< 1e–5
β_8	–0.00005	0.00001	–7.66937	< 1e–5

The coefficient of determination equals 0.993, and the standard deviation of the residuals equals 758.24. At the significance level $\alpha = 0.05$, the H_0 hypothesis was rejected in favor of H_1 for the structural parameters of $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8$, therefore the predictors of these parameters significantly affect the polynomial trend in the time series. The value of the statistic for the Ramsey RESET test is 0.9118, while the p-value is 0.5895.

Consistently, in a further step, a model was built for data covering the time of the pandemic (red line in Fig. 2). Table 5 presents structural parameters, standard deviations of parameters, values of t-statistics and p-values for the entire period.

The coefficient of determination is equal to 0.9921, and the standard deviation of the residuals is 825.34. At the significance level $\alpha = 0.05$, the H_0 hypothesis was rejected in favor of H_1 for the $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8$. parameters. Thus, also in this case, the predictors at these parameters significantly affect the polynomial trend in the time series.

Table 5. Structural parameters, standard errors, values of t-statistic and p-value for the trend to the entire period

	Estimate	Std. Error	t value	p-value
β_0	801.28414	2682.23759	0.29874	0.76771
β_1	9504.78508	3121.59039	3.04485	0.00558
β_2	–4600.55486	1230.83189	–3.73776	0.00102
β_3	1068.95081	230.10187	4.64555	0.00010
β_4	–127.14660	23.38380	–5.43738	0.00001
β_5	8.31891	1.36469	6.09581	< 1e–5
β_6	–0.30269	0.04564	–6.63143	< 1e–5
β_7	0.00574	0.00081	7.06237	< 1e–5
β_8	–0.00004	0.00001	–7.40639	< 1e–5

For polynomials constructed for CO_2 emitted from passenger vehicles, their parameters were similarly compared. Table 6 presents the estimated values of statistics (6) and p-values for the test of differences of structural parameters.

Table 6. T-statistic values and p-value for the tests of differences of structural parameters

	T	p-value
β_0	–2.22406	0.02614
β_1	2.79922	0.00512
β_2	–3.30850	0.00094
β_3	3.76942	0.00016
β_4	–4.18986	0.00003
β_5	4.57649	< 1e–5
β_6	–4.93458	< 1e–5
β_7	5.26820	< 1e–5
β_8	–5.58048	< 1e–5

At the significance level $\alpha = 0.05$, the H_0 hypothesis was rejected in favor of H_1 for all structural parameters. The parameters are significantly different for the polynomial trend determined for the CO_2 emission series up to the pandemic and the polynomial trend determined for the CO_2 emission series containing the first year of the pandemic. Thus, in the case of passenger cars, the COVID-19 pandemic has significantly affected the trend in CO_2 emissions.

3.3. Light and heavy duty trucks

Trucks, which are the second largest group of vehicles registered in Poland [19, 26, 35] were then examined. As of the end of 2021, the number of registered trucks (including goods and passenger carrying vehicles) will reach 3.6 million [30], 3.0% more than a year ago. CO_2 emissions from light duty tracks (black line in Fig. 3) and heavy duty trucks (black line in Fig. 4) were analyzed.

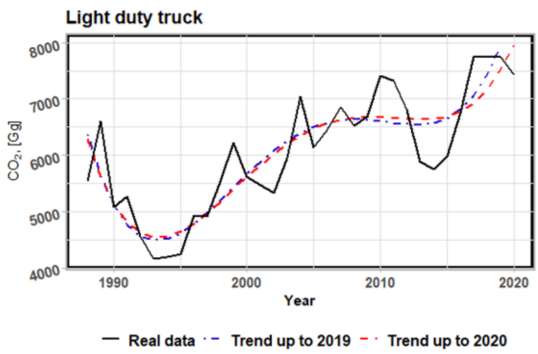

Fig. 3. CO_2 emissions for light duty truck [8]

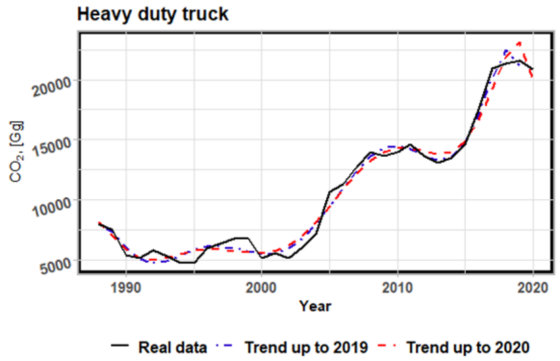

Fig. 4. CO_2 emissions for heavy duty trucks [8]

The models built for the pre-pandemic period (blue line in Fig. 3 and 4), their structural parameters, standard deviations of the parameters, values of the t-statistic and p-values are presented in Table 7.

Table 7. Structural parameters, standard errors, values of t-statistic and p-value for the trend to the pre-pandemic period

	Estimate	Std. error	t value	p-value
	Light duty truck			
β_0	7347.38426	585.58715	12.54704	< 1e–5
β_1	–1103.45576	237.77329	–4.64079	0.00008
β_2	136.30530	28.67462	4.75352	0.00006
β_3	–5.78733	1.29616	–4.46498	0.00013
β_4	0.08198	0.01950	4.20497	0.00026
	Heavy duty truck			
β_0	5669.98087	2480.91621	2.28544	0.03183
β_1	4898.82097	2959.13457	1.65549	0.11141
β_2	–3354.68039	1198.06785	–2.80008	0.01017
β_3	850.59185	230.29124	3.69355	0.00120
β_4	–106.96717	24.08233	–4.44173	0.00019
β_5	7.34736	1.44699	5.07767	0.00004
β_6	–0.27943	0.04984	–5.60608	0.00001
β_7	0.00552	0.00091	6.03490	< 1e–5
β_8	–0.00004	0.00001	–6.37530	< 1e–5

For CO_2 emissions from light duty trucks, the coefficient of determination is equal to 0.7679 and the standard deviation of the residuals is 542.63. At the significance level $\alpha = 0.05$, it was found that the structural parameters $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$ are significantly different from zero (Table 7), thus, the predictors of these parameters significantly affect the polynomial trend in the time series. The value of the statistic for the Ramsey RESET test is 2.1032, while the p-value is 0.0877.

At the significance level $\alpha = 0.05$ for heavy duty trucks, it was found that parameters $\beta_0, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8$ are significantly different from zero (Tab. 7), thus predictors at these parameters significantly affect the trend of CO_2 emissions. The value of the statistic for the Ramsey test is 1.4937, while the p-value is 0.305. The coefficient of determination is higher and equal to 0.9856. The standard deviation of the residuals, meanwhile, is 731.88.

The models built for the entire study period (red line in Fig. 3 and 4), their structural parameters, standard deviations, t-statistic values and p-values are presented in Table 8.

Table 8. Structural parameters, standard errors, values of t-statistic and p-value for the trend for the entire period

	Estimate	Std. error	t value	p-value
	Light duty truck			
β_0	7166.73855	585.40978	12.24226	< 1e–5
β_1	–993.26539	230.94782	–4.30082	0.00019
β_2	119.85381	27.04951	4.43091	0.00013
β_3	–4.92894	1.18699	–4.15246	0.00028
β_4	0.06762	0.01733	3.90227	0.00055
	Heavy duty truck			
β_0	8345.93187	2968.73528	2.81128	0.00967
β_1	931.14915	3455.01664	0.26951	0.78984
β_2	–1480.57710	1362.30067	–1.08682	0.28791
β_3	445.58876	254.67973	1.74960	0.09296
β_4	–60.51175	25.88150	–2.33803	0.02805
β_5	4.33818	1.51046	2.87209	0.00839
β_6	–0.16909	0.05052	–3.34697	0.00269
β_7	0.00338	0.00090	3.76141	0.00096
β_8	–0.00003	0.00001	–4.11824	0.00039

For CO_2 emissions from light duty trucks, the coefficient of determination for the entire study period is 0.7621 and the standard deviation of the residuals is 554.42. At the significance level $\alpha = 0.05$, thus all parameters of the model are significantly different from zero. For the trend model of CO_2 emissions generated by heavy duty trucks, the coefficient of determination is 0.9792, and the standard deviation of the residuals is 913.5. At the significance level $\alpha = 0.05$, it was found that the structural parameters $\beta_0, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8$ significant are different from zero, thus the predictors at these parameters significantly affect the trend occurring in the time series.

Comparing the two models with each other for each of the modes of transport analyzed, it can be seen again that the COVID-19 pandemic also affected the trend of CO_2 emissions from trucks. Table 9 presents the values of statistic (6) and p-values for the test of differences in the structural parameters. For light duty trucks at the significance level $\alpha = 0.05$, the H_0 hypothesis was rejected in favor of H_1 for the structural parameters β_2, β_3, β_4, while for heavy duty trucks the parameters β_0, β_1, β_2, β_3, β_4, β_5, β_6, β_7, β_8 are significantly different for the polynomial trend determined for the CO_2 emission series up to the pandemic and the polynomial trend determined for the CO_2 emission series containing the first year of the pandemic.

Table 9. T-statistic values and p-value for the tests of differences of structural parameters

	T	p-value		T	p-value
	Light duty truck			Heavy duty truck	
β_0	1.14388	0.25267	β_0	–3.35853	0.00078
β_1	–1.74252	0.08142	β_1	4.23413	0.00002
β_2	2.18704	0.02874	β_2	–5.01350	< 1e–5
β_3	–2.55875	0.01051	β_3	5.72280	< 1e–5
β_4	2.88339	0.00393	β_4	–6.37357	< 1e–5
			β_5	6.97556	< 1e–5
			β_6	–7.53647	< 1e–5
			β_7	8.06220	< 1e–5
			β_8	–8.55730	< 1e–5

3.4. Motorcycles

The analyses conducted ended with a study of motorcycles. Despite their growing popularity — 23,910 new motorcycles were registered in 2022, 10.8% more than in the previous year [30, 35]. It is clear that CO_2 emissions have been on a downward trend over the years (black line Fig. 5).

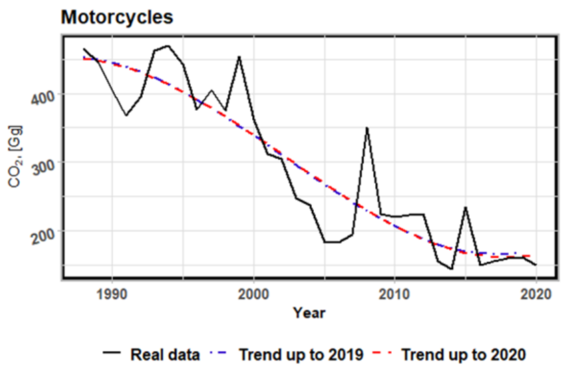

Fig. 5. CO_2 Emission for Motorcycles [8]

The estimators of parameters of the model constructed for the pre-pandemic period (blue line in Fig. 5), standard deviations of parameters, t-statistics and p-values are presented in Table 10.

Table 10. Structural parameters, standard errors, values of t-statistic and p-value for the trend to the pre-pandemic period

	Estimate	Std. error	t value	p-value
β_0	452.59779	17.62924	25.67313	< 1e–5
β_2	–0.94515	0.16588	–5.69780	< 1e–5
β_3	0.02087	0.00535	3.90082	0.00052

The coefficient of determination is 0.8293 and the standard deviation of the residuals is 48.66. At the significance level $\alpha = 0.05$, the H_0 hypothesis was rejected in favor of H_1 for the structural parameters β_0, β_2, β_3, thus the predictors of these parameters significantly affect the polynomial trend in the time series. The value of the statistic for the Ramsey RESET test is 1.3867, while the p-value is 0.2638.

The estimator of model parameters for the entire study period (red line in Fig. 5), standard deviations of parameters, t-statistics and p-values are presented in Table 11.

Table 11. Structural parameters, standard errors, values of t-statistic and p-value for the trend to the entire period

	Estimate	Std. error	t value	p-value
β_0	451.31832	17.10369	26.38718	< 1e–5
β_2	–0.91973	0.15152	–6.07003	< 1e–5
β_3	0.01992	0.00474	4.20027	0.00022

The coefficient of determination is 0.8368, and the standard deviation of the residuals is 47.97. At the significance level $\alpha = 0.05$, the H_0 hypothesis was rejected in favor of H_1 for the structural parameters β_0, β_2, β_3, thus the predictors at these parameters significantly affect the polynomial trend in the time series.

Comparing the parameters of the models for each period this time led to different conclusions. At the significance level $\alpha = 0.05$, there is no basis to reject the H_0 hypothesis for all structural parameters. Thus, the parameters are not significantly different for the polynomial trend determined for the CO_2 emission series up to the pandemic and the polynomial trend determined for the CO_2 emission series containing the first year of the pandemic. The trend parameters of the period up to the pandemic and the period with the onset of the pandemic are not significantly different, thus there was no significant effect on the trend. Table 12 presents the values of statistic (6) and p-values for the structural parameter difference test.

Table 12. T-statistic values and p-value for the tests of differences of structural parameters

	T	p-value
β_0	0.28281	0.77732
β_2	–0.61391	0.53927
β_3	0.72418	0.46895

This result of the study of CO_2 emissions from motorcycles is probably due to the fact that traveling on a motorcycle was not associated with an increased risk of danger, as all single-track vehicles were a safe means of transport from the point of view of virus infection. This is why the result is so different from other modes of transport.

4. Conclusion

The primary objective of the study was to assess whether the COVID-19 pandemic significantly affected CO_2 emissions from road transport. A general analysis was made first, without distinguishing between different modes of transport, and then passenger cars, light and heavy-duty trucks and motorcycles were examined. It turned out that only in the case of motorcycles was the impact of the pandemic not significant. Thus, global mobility restrictions and probably the fear of becoming infected have influenced public behavior. Despite the woeful pandemic period, meaningful conclusions can also be drawn. The study shows that changes are possible regarding CO_2 emissions from transport, but they require comprehensive, systemic solutions.

The obtained results clearly prove that it is possible to implement mechanisms for controlling society on a global scale and to achieve the desired results in terms of harmful emissions. The solutions implemented in this area require the use of appropriate analysis methods that will allow for a reliable assessment of whether the implemented changes bring the expected results and whether the obtained effect is statistically significant. The method proposed in the article can be successfully used for such analyses. The algorithm proposed in the methodological chapter is universal and can also be applied to factors other than the COVID-19 pandemic. This is an additional advantage of the article.

In early 2023, the European Parliament approved new targets to reduce CO_2 emissions produced by new passenger and goods carrying vehicles by 100 percent by 2035 compared to 2021. With regard to the results presented, these assumptions seem difficult to implement. Over the entire period studied, for every mode of transport except motorcycles, the research presented shows an upward trend. Only the COVID-19 pandemic caused small declines but only for passenger cars and heavy duty trucks. Thus, changes in this area are necessary. Given the short time left for Poland and the European Union as a whole to achieve climate neutrality, it is necessary to introduce the principles of sustainable development and take a holistic view of the environmental impact of individual modes of transport.

In the article, the study was conducted at a general level, observing global trends and considering whether they are possible to change. This provides the basis for more detailed analyzes and the search for relationships between specific solutions and CO_2 emissions.

In addition, due to the fact that the publication of emissions data is delayed, so the authors have not had the opportunity to make a study based on complete historical data, it is necessary to continue research and analyze trends. However, this will be the direction of further research planned in this area.

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