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Research article

The impact of COVID-19 vaccination on human mobility: The London case

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A R T I C L E   I N F O

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A B S T R A C T

The COVID-19 pandemic has become a global public health crisis, causing significant morbidity and mortality worldwide. As an early response, different lockdowns were imposed in the UK (and the world) to limit the spread of the disease. Although effective, these measures profoundly impacted mobility patterns across cities, significantly reducing the number of people commuting to work or travelling for leisure. As different governments introduced massive vaccination programs to tackle the pandemic, cities have significantly but slowly increased human mobility, enabling the resumption of travel, work, and social activities. Nevertheless, how much can this return to normal mobility patterns be attributed to vaccines? In this study, we answer this question using a statistical approach, analysing two different open urban mobility datasets to quantify the effect vaccination rollouts have had on increased human activities.

1. Introduction

In light of the COVID-19 pandemic, public health authorities worldwide initially responded with different restrictive, non-pharmaceutical measures, from promoting the washing of hands to restricting the movement of people and establishing different rules concerning where and for what purposes people can meet and interact [1–6]. These restrictive measures have profoundly impacted human mobility across several cities around the world [7–9]. Particularly, in the UK, at its most restrictive phase (26th March 2020 to 21st June 2020), only essential workers were allowed to travel to work [10], which accounts for roughly only 20% of the population [11].

From the early stages of the pandemic, vaccination emerged as the most viable, permanent solution to contain, if not the number of infections, the number of hospitalisations that was one of the most pressuring factors worldwide [12–17]. The COVID-19 vaccines effectively prevent severe illness, hospitalisation and death. Vaccination protects the individual and contributes to community immunity, which can help control the spread of the virus. By December 2020, the UK government set up a vaccine delivery plan to ensure the general population would have access to a safe and effective vaccine against COVID-19 [18]. Phase one offered only the vaccine to those aged 50 and over and those in clinical risk groups. From April 2021, the vaccine was offered to adults aged 18 to 49. Later

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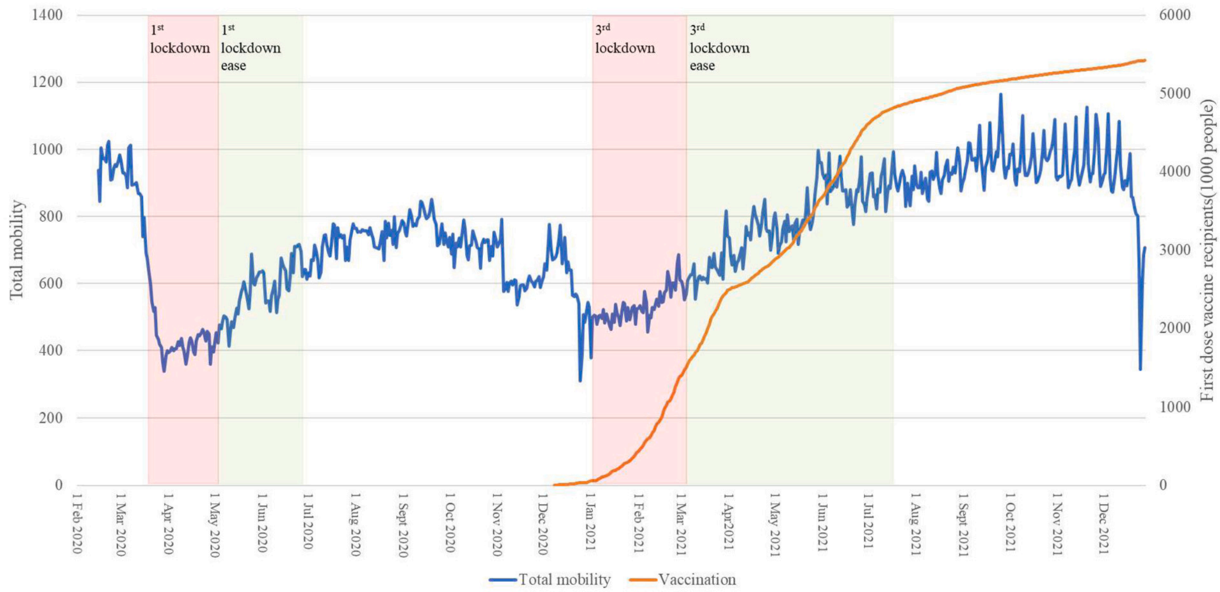

Fig. 1. The change of mobility and vaccination in London. The total mobility corresponds to the aggregated Google and Apple daily counts. We can observe an increase in mobility from June 2021, around the same time the UK vaccination program peaked. No causation is implied at this point. Nevertheless, a positive correlation is observed. Prepared by the authors from: Apple [27], Google [28], UK Health Security Agency [35].

that same year, aiming to maintain protection against COVID-19, a booster program took place to deliver new vaccine doses in the winter of 2021.

Vaccination programs had a positive impact in reducing the number of hospitalisation worldwide [19,20]. Particularly in England [21,22], the positive effect of this vaccination program and the easing of restricting measures was clear by March 2021, when a substantial drop in COVID-19-related hospitalisations was observed while the number of vaccinated people incrementally raised. However, this positive effect was observed not only in the number of hospitalisations but in the movement of people, as shown in Fig. 1. Previous research has already shown a link between vaccines and mobility, plus easing restrictions and COVID fatigue [23,24].

This study examined the linkage between human mobility and vaccination in the context of the COVID-19 pandemic [25,26].

We hypothesise that the reduction in COVID-19 cases does not fully explain the change in mobility. To test our hypothesis, we propose a regression model to explain the change in daily mobility based on the number of people vaccinated, the number of COVID-19 cases and the average daily temperature.

We organise the rest of this paper as follows: first, we review different human mobility patterns during the years 2020 and 2021, using as proxy Apple and Google mobility data; in section three, we propose two different linear regression models to measure the impact of the vaccination program and compare our results against a Null model; finally, we explore our results compared them against actual data drawing a set of conclusions and future directions.

2. Data

2.1. Mobility data

After the outbreak of the COVID-19 pandemic, Apple [27] and Google [28] released daily mobility figures that and has been extensively used as a proxy for transport activities in current studies [29–34]. The Apple data have three categories of human mobility: driving, transit and walking (Fig. 2), while the Google data includes six categories: retail and recreation (R&R), grocery and pharmacy (G&P), parks, transit stations (TS), workplaces and residential. In this work, to generally understand the mobility changes induced by vaccinations, we focus on transport mode instead of a type of location and group all categories of mobility from Apple and Google as the total mobility.

This increase in the mobility change ratio happened at a different rate for all transport modes. Plotting each mode individually (Fig. 2), we can trace the changes by mode and their relationship with the differences between the 1st and 3rd lockdowns after the loosening of travel restriction policies. When the 1st lockdown began to ease in London, the recovery speed of Driving mobility was the fastest, followed by Walking, and finally, Transit. There are obvious gaps between the three modes, and Driving tends to widen the gap with the other two modes. However, the situation was different during the third lockdown easing. Driving recovered the fastest at first, followed by Transit and Walking, which are about the same. During this time, Driving did not widen the gap with the other two modes, and even the growth in the mobility of the other two modes finally surpassed that of Driving. Also, we find that compared with the first lockdown and lockdown ease period, people tend to take more trips after the vaccination programme starts in London. It should be noted that, unlike the 1st lockdown, the entire 3rd lockdown period followed the launch of the vaccination programme.

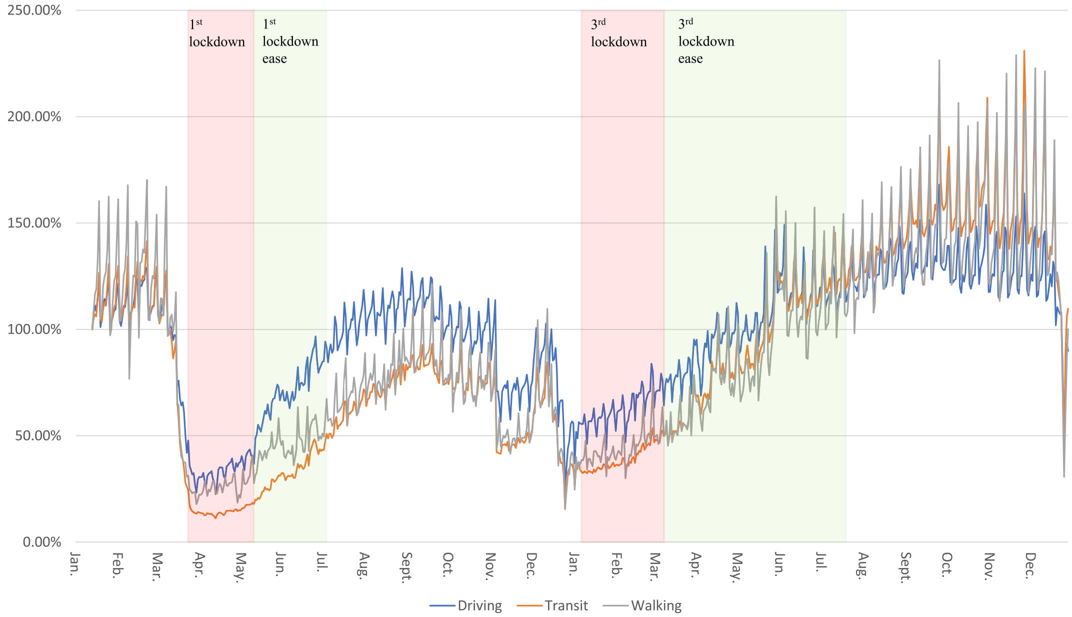

Fig. 2. Mobility for the three transportation modes in London in 2020 and 2021. The shaded areas represent the different lockdown stages. It is clear the abrupt drop in mobility counts when the first lockdown was declared and how slow it tried to recover during the No-lockdown periods. The increase in mobility since the beginning of the 3rd lockdown led to the typical pattern observed in December 2019, before the start of the Pandemic. Prepared by the authors from: Apple [27], UK Health Security Agency [35].

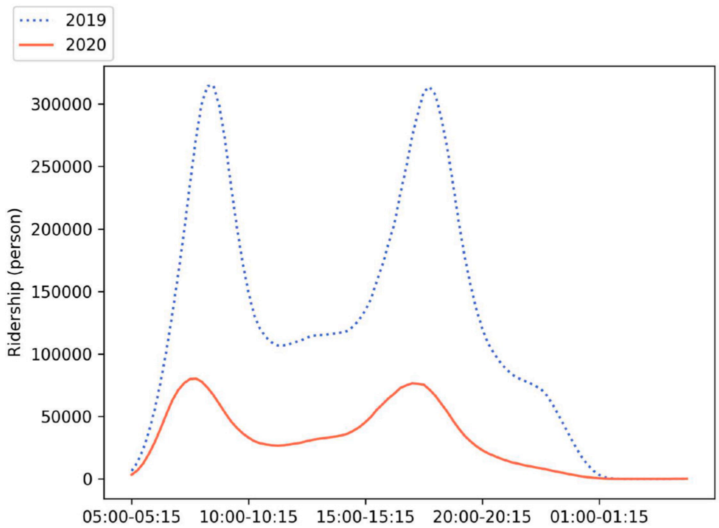

Fig. 3. Underground ridership in London in 2019 and 2020. Prepared by the authors from: TfL [36].

We originally planned to compare the changes in mobility between 2019 and subsequent years to clarify the link between the epidemic, vaccinations, and travel. However, neither Apple nor Google provided mobility data before the epidemic. So we used data from the London Underground to show how people's travel changed before and after the epidemic. The data we use comes from a database developed by TfL [36], and the raw data includes the average number of people entering and leaving the station every 15 minutes a day at each station in London in a certain year. We add up the number of people entering and leaving the station at each period at all stations to represent the average ridership of the London Underground in that period (Fig. 3). From the figure, we find that the ridership of the London Underground in 2020 has declined significantly compared with that in almost all periods in 2019. The most severe decline occurred during the morning and evening rush hours, making the peak ridership of the underground appears more moderate compared to noon in 2020.

Table 1
Descriptive statistics for the input data.

Stage	N	Variable	Mean	Median	Std Dev	Min	Max
1st lockdown	46	Driving (%)	33.87	33.91	4.99	22.54	43.56
		Transit (%)	14.51	14.11	1.71	11.21	18.45
		Walking (%)	26.28	26.25	4.56	17.83	40.92
		Driving/Transit	2.33	2.38	0.20	1.75	2.70
		Walking/Transit	1.82	1.80	0.27	1.27	2.36
		Vac (person)	0.00	0.00	0.00	0.00	0.00
		COVID (person)	532.50	510.00	253.95	123.00	1063.00
		Temp (°C)	12.25	12.35	3.14	5.30	17.60
1st lockdown ease	55	Driving (%)	70.88	70.69	12.92	40.83	96.68
		Transit (%)	32.91	31.34	8.53	18.60	50.91
		Walking (%)	46.32	44.90	8.30	28.94	67.33
		Driving/Transit	2.20	2.20	0.21	1.80	2.65
		Walking/Transit	1.45	1.38	0.23	1.14	2.11
		Vac (person)	0.00	0.00	0.00	0.00	0.00
		COVID (person)	67.49	52.00	42.44	22.00	203.00
		Temp (°C)	16.85	17.40	3.43	9.20	24.90
3rd lockdown	62	Driving (%)	63.18	62.28	8.27	43.39	83.80
		Transit (%)	39.48	36.65	6.10	32.37	53.59
		Walking (%)	44.89	42.91	7.80	29.99	73.42
		Driving/Transit	1.61	1.65	0.13	1.29	1.85
		Walking/Transit	1.14	1.12	0.11	0.85	1.45
		Vac (person)	678100.65	561603.50	488739.57	80006.00	1627104.00
		COVID (person)	3636.87	2023.00	3566.30	416.00	13885.00
		Temp (°C)	5.94	6.30	3.61	−0.80	13.70
3rd lockdown ease	62	Driving (%)	104.24	104.10	18.33	65.83	149.11
		Transit (%)	94.77	92.75	27.24	48.39	150.00
		Walking (%)	90.41	86.18	27.57	45.28	162.50
		Driving/Transit	1.14	1.12	0.18	0.82	1.55
		Walking/Transit	0.96	0.95	0.08	0.79	1.21
		Vac (person)	3322979.56	3143611.00	930899.50	1655679.00	4831843.00
		COVID (person)	1172.77	457.00	1563.08	183.00	7817.00
		Temp (°C)	13.29	11.80	4.79	3.50	24.40

2.2. Vaccination and COVID case data

To measure the severity of the COVID-19 pandemic, we use the daily number of new COVID-19 cases in London as an independent variable in our model. The case data are drawn from the coronavirus in the UK dashboard developed by the UK Health Security Agency [35]. This dashboard provides up-to-date and authoritative information about the COVID-19 pandemic. From this data, we only considered people aged between 12 and 69 who received the first vaccine dose in London. Younger and older people, due to physical limitations, lack of commuting purposes or smartphones, are misrepresented in Apple data.

2.3. Temperature data

As this study uses daily time series data for a region with an overall time span of two years, and the regressions and causality test uses a period of less than one year, we assume that factors such as London's demographics, infrastructure, and economic indicators do not change over the study period, excluding them as influences on mobility. However, seasonal changes are more sensitive to temporal changes. Therefore, for time series data, special attention needs to be paid to seasonal changes. On the one hand, the two lockdowns studied in this research each span different months of a year, and that time span is long enough to cause significant changes in temperature. On the other hand, the weather is another important factor that could influence human activity [37–39]. Thereby, We use the daily average temperature in London as a variable in our model as a proxy of weather. Our temperature data is from the official weather station at St James' Park in London, obtained by Meteomanz [40].

The model introduced in the next section uses the mobility (by transport mode), vaccination, temperature and COVID cases data described as input. Table 1 shows the descriptive statistics for these variables during the different lockdown stages in the UK. The mean and median values give an approximate picture of the situation over the period. Compared with the first lockdown and lockdown ease period, people tend to take more trips after the vaccination programme starts in London. As in Fig. 1, the observed variables follow the logic of these stages, incrementing their values over time. For example, the mean for walking during the 1st lockdown is 26.29, increasing to 90.41 at the 3rd lockdown ease. It's notable that the number of vaccinated population is zero for the first 1st lockdown and its ease.

3. Methods

3.1. Regression model

To determine the relationship between the vaccination campaign and London's human mobility, a classic Linear Regression model is established in our study [41]. Linear regression has good interpretability because it can demonstrate a simple linear relationship between the independent and dependent variables through the coefficients of the variables in the model. Also, due to its simplicity, linear regression is an easy-to-use model. Because of these characteristics, empirical studies focusing on transportation during epidemics also favour this method [42–46]. It should be noted that the linear regression model needs to focus on the goodness of fit, the normality of residuals, the homogeneity of variance, and multicollinearity to ensure that the model is effective and unbiased. The validated model can draw easily interpretable conclusions from regression coefficients, coefficient significance, model significance, goodness of fit, and other aspects.

In this case, they can help us identify potential causal relationships between vaccination and transportation modes during 1st and 3rd lockdown stages.

We can express the relationship between our variables as follows:

$$M_t = \Phi X_t + \Sigma_t \tag{1}$$

where

$$M_t = \begin{bmatrix} Driving_t \\ Transit_t \\ Walking_t \\ Driving_t/Transit_t \\ Walking_t/Transit_t \end{bmatrix}, \qquad X_t = \begin{bmatrix} Vac_{t-3} \\ COVID_t \\ Temp_t \end{bmatrix}.$$

Φ is the coefficient matrix and Σ_t are the regression errors. The Vector X_t is the model's input (independent variables), composed by:

- Vac_{t-3} - Cumulative number of people aged between 12 and 69 who received the first vaccination dose on the day $t-3$. The 12 to 69 restriction is due to physical limitations and the lack of commuting purposes that make younger children and older people travel less.
- $COVID_t$-The number of daily new COVID cases on day t.
- $Temp_t$-Average temperature (°C) on day t. The two lockdown stages analysed span several months and have seasonal differences, so we use $Temp$ to control seasonal factors.

As in any standard linear model, we will use X_t as an explanatory vector at t.

In addition to the observed data, we developed two new dependent variables, $Driving_t/Transit_t$ and $Walking_t/Transit_t$, which are referred to as mobility ratio in our study. We use this ratio to observe the relative changes between driving and transit mobility and between walking and transit mobility.

Based on the UK's lockdown phases, we ran separate regressions using the following two samples:

- Sample 1 for lockdown phases one and three
- Sample 2 for ease phases one and three

3.2. Null model

To provide a baseline against which our results can be compared, we define the null model in Eq. (2)

$$M_t = \psi X_t^{null} + \Sigma_t^{null} \tag{2}$$

where X_t^{null} denotes the explanatory vector at time t; Ψ, the coefficient matrix; and Σ_t^{null} denotes the regression errors. In this case, X_t^{null} does not include the variable Vac_{t-3}, assuming that vaccination has no effect or relationship with mobility.

In addition to our models, we conducted a causality analysis based on the Toda-Yamamoto to further explore the relation between vaccinations and mobility methods.

3.3. Toda-Yamamoto causality test

In most real-life phenomena, it is incorrect to directly test the causal relationship between variables, such as Granger causality testing between inappropriate time series [47]. The Toda-Yamamoto causality test has been proposed as a robust alternative to extracting causal relationships between time series [48], which adds additional lags instead of requiring variables to be stationary or cointegrated [49–51]. In this study, the formulation of augmented VAR is shown as follows:

$$
\begin{aligned}
lnMobility_t &= C_1 + \sum_{i=1}^{p+d_{max}} \alpha_{1i} lnMobility_{t-i} + \sum_{i=1}^{p+d_{max}} \beta_{1i} lnVac_{t-i} + \sum_{i=1}^{p+d_{max}} \gamma_{1i} lnCOVID_{t-i} + \epsilon_{1t} \\
lnVac_t &= C_2 + \sum_{i=1}^{p+d_{max}} \alpha_{2i} lnMobility_{t-i} + \sum_{i=1}^{p+d_{max}} \beta_{2i} lnVac_{t-i} + \sum_{i=1}^{p+d_{max}} \gamma_{2i} lnCOVID_{t-i} + \epsilon_{2t} \\
lnCOVID_t &= C_3 + \sum_{i=1}^{p+d_{max}} \alpha_{3i} lnMobility_{t-i} + \sum_{i=1}^{p+d_{max}} \beta_{3i} lnVac_{t-i} + \sum_{i=1}^{p+d_{max}} \gamma_{3i} lnCOVID_{t-i} + \epsilon_{3t}
\end{aligned}
\tag{3}
$$

where $Mobility$ represents the sum of Apple mobility and Google mobility. p is the optimal lag length of original var model, d_{max} is the maximal order of integration of the variables. ϵ is the error term. The Toda-Yamamoto method is based on the null hypothesis expressed as zero restrictions on the coefficients of the augmented VAR model. For example, reject the null hypothesis that $\gamma_{11} = \gamma_{12} = \cdots = \gamma_{1p} = 0$ implies a unidirectional causality from the COVID cases to the overall mobility. Afterwards, we can determine whether to reject these null assumptions about coefficients by detecting the Wald statistic (χ^2).

For the Toda-Yamamoto test, we used the daily data from 6th January 2021 to 31st October 2021 for London, as the 6th was the start of the third lockdown in England, and the UK vaccination programme started before December 2020.

For all our analyses, we used the SPSS (version 26.0) and EVIEWS (version 10.0) statistical software.

4. Results and discussion

4.1. Regression model

We first performed logarithmic transformation on all variables to ensure the normality and homogeneity of variance of the model residuals. Table 2 shows the regression results of Eq. (1). As we can see from the result of Sample 1, the Vac (Vac_{t-3} variable) term has a positive and significant effect on the mobility of driving, transit and walking (i.e., the Apple mobility), with transit being the most affected. For every 0.1 increase in lnVac, lnTransit will increase by 0.0086%. As for Google mobility, results show that the Vac term positively influenced the mobility of R&R, G&P, Parks, TS and workplaces while negatively affecting the mobility of residential. For the COVID variable, the results indicate that additional new COVID cases are negatively associated with the mobility of driving, transit, walking, R&R, G&P, parks, TS, and workplaces.

According to the regression results of Sample 2, the vaccination progress has a significant and positive impact on all types of mobility except for residential mobility. In addition, it can be seen that transit mobility is most affected by vaccination, as it has the largest lnVac coefficient and for every 0.1 increase in lnVac, the transit mobility rate increases by 0.009%. Moreover, the daily new COVID cases are found to be negatively associated with all types of mobility except for residential mobility.

Furthermore, it is worth noting that the temperature impact in Sample 2 is relatively more significant than in Sample 1, indicating that people tend to consider temperature factors more during the lockdown ease phase.

As described in Section 2, changes in how people travel were observed during the first and third lockdown ease stage, and the results of descriptive statistics confirmed this change. We also want to explore the relationship between these changes and vaccination. Therefore, we used the ratio of driving mobility to transit mobility and walking mobility to transit mobility as the dependent variable to run the regressions, respectively, and the results are shown in Table 3. According to our results, vaccination progress at the lockdown ease stage negatively impacted these two ratios at the 1% significance level. Furthermore, the results indicate that the additional daily new COVID cases would significantly increase both ratios. The results also showed that the impact of vaccination on $Driving/Transit$ was greater than on $Walking/Transit$, and for every 0.1 increase in lnVac could lead to a 0.0082 reduction in the $Driving/Transit$.

In addition, several diagnostic tests were performed to evaluate the validity of the regression model. First, we tested multi-collinearity for each variable. The variance inflation factor (VIF) for $lnVac_{t-3}$, $lnCOVID$ and $lnTemp$ in Sample 1 is 1.684, 1.648, and 1.463, and in Sample 2, it is 4.444, 3.975, and 1.622, respectively. The VIF values for all variables in both samples are lower than 5, indicating insufficient evidence of collinearity between variables.

Second, a normal probability plot like the one in Fig. 4 was plotted for each model to check whether the model residuals followed a normal distribution. The closer the distribution of the scatter is to the straight line in the graph, the closer the distribution of the residuals is to the normal distribution.

Third, We also plotted residual vs predicted values for each model to observe whether the model follows the same variance assumption. As shown in Fig. 5, the model does not have heteroscedasticity if scattering points are randomly distributed within a certain residual range.

Finally, in Appendix A, we compare our model with the null model regarding the observed versus modelled trends. All of the diagnostic plots of the other models are shown in Appendix B.

4.2. Null model

Table 4 displays the outcomes of the null model. The results show that once the variable Vac_{t-3} was removed, each model's adjusted r-squared dropped significantly for both samples. Adjusted r-squared is used to measure the goodness of fit of the regression model while considering the effect of the number of variables on the fitting. In this case, the value of the adjusted r-squared increases

Table 2
Regression results with the mobility as the dependent variable for the two sample groups.

Dependent variable	Independent variable	Sample 1			Sample 2		
		Coef.	Std.Error	Std.Coef.	Coef.	Std.Error	Std.Coef.
lnDriving	Constant	3.764***	0.099		3.295***	0.080	
	lnVac	0.056***	0.002	1.054	0.042***	0.003	1.114
	lnCOVID	−0.049***	0.012	−0.166	−0.048***	0.014	−0.263
	lnTemp	0.020	0.017	0.046	0.407***	0.033	0.583
	Adjusted R^2	0.891			0.735		
lnTransit	Constant	3.068***	0.064		1.823***	0.118	
	lnVac	0.086***	0.001	1.081	0.090***	0.004	1.089
	lnCOVID	−0.069***	0.008	−0.157	−0.043**	0.020	−0.107
	lnTemp	0.011	0.011	0.017	0.645***	0.050	0.419
	Adjusted R^2	0.979			0.880		
lnWalking	Constant	3.526***	0.114		2.265***	0.115	
	lnVac	0.053***	0.003	1.079	0.057***	0.004	0.969
	lnCOVID	−0.063***	0.014	−0.234	−0.018	0.020	−0.064
	lnTemp	0.049**	0.020	0.121	0.580***	0.048	0.526
	Adjusted R^2	0.829			0.779		
lnR&R	Constant	3.140***	0.107		2.234***	0.100	
	lnVac	0.045***	0.002	1.021	0.052***	0.004	1.025
	lnCOVID	−0.039***	0.013	−0.160	−0.030*	0.017	−0.125
	lnTemp	0.025	0.019	0.068	0.483***	0.042	0.514
	Adjusted R^2	0.817			0.768		
lnG&P	Constant	4.410***	0.069		4.113***	0.033	
	lnVac	0.018***	0.002	0.940	0.015***	0.001	1.032
	lnCOVID	−0.040***	0.009	−0.379	−0.011**	0.006	−0.159
	lnTemp	0.003	0.012	0.022	0.111***	0.014	0.403
	Adjusted R^2	0.586			0.705		
lnParks	Constant	4.701***	0.196		4.190***	0.130	
	lnVac	0.023***	0.004	0.573	0.010**	0.005	0.301
	lnCOVID	−0.094***	0.024	−0.426	−0.053**	0.022	−0.317
	lnTemp	0.100***	0.034	0.305	0.323***	0.055	0.502
	Adjusted R^2	0.245			0.161		
lnTS	Constant	3.448***	0.071		2.746***	0.072	
	lnVac	0.033***	0.002	1.099	0.040***	0.003	1.159
	lnCOVID	−0.058***	0.009	−0.348	−0.050***	0.012	−0.304
	lnTemp	0.017	0.012	0.067	0.361***	0.030	0.565
	Adjusted R^2	0.829			0.739		
lnWorkplaces	Constant	3.909***	0.222		3.120***	0.162	
	lnVac	0.043***	0.005	0.789	0.042***	0.006	0.886
	lnCOVID	−0.080***	0.028	−0.264	−0.082***	0.028	−0.360
	lnTemp	−0.031	0.039	−0.069	0.344***	0.068	0.393
	Adjusted R^2	0.475			0.305		
lnResidential	Constant	4.752***	0.040		4.978***	0.029	
	lnVac	−0.006***	0.001	−0.713	−0.010***	0.001	−1.058
	lnCOVID	0.017***	0.005	0.351	0.018***	0.005	0.379
	lnTemp	0.002	0.007	0.024	−0.087***	0.012	−0.482
	Adjusted R^2	0.329			0.493		

Note: *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

Table 3
Regression results with the mobility ratio as the dependent variable for Sample 2.

Dependent variable	Independent variable	Coef.	Std.Error	Std.Coef.
Driving/Transit	Constant	3.002***	0.086	
	lnVac	−0.082***	0.003	−1.082
	lnCOVID	0.029**	0.015	0.079
	lnTemp	−0.327***	0.036	−0.232
	Adjusted R^2	0.925		
Walking/Transit	Constant	1.545***	0.084	
	lnVac	−0.041***	0.003	−1.052
	lnCOVID	0.039***	0.014	0.203
	lnTemp	−0.089**	0.035	−0.122
	Adjusted R^2	0.730		

Note: *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

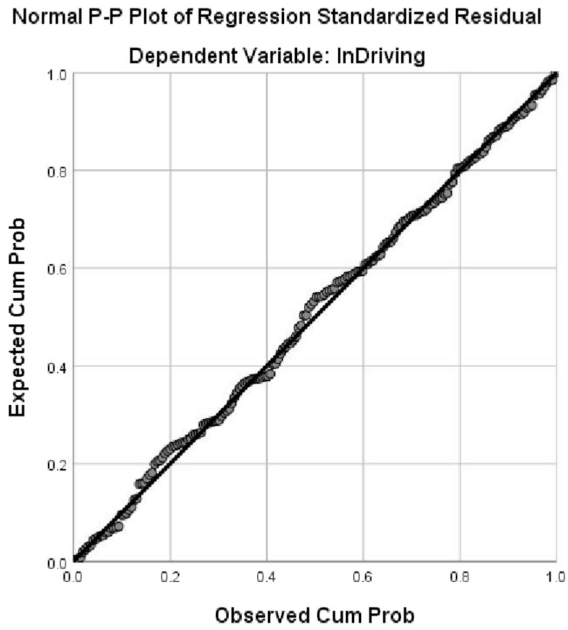

Fig. 4. Residual Normal Probability Graph of the Model with lnDriving as the Dependent Variable in Sample 2.

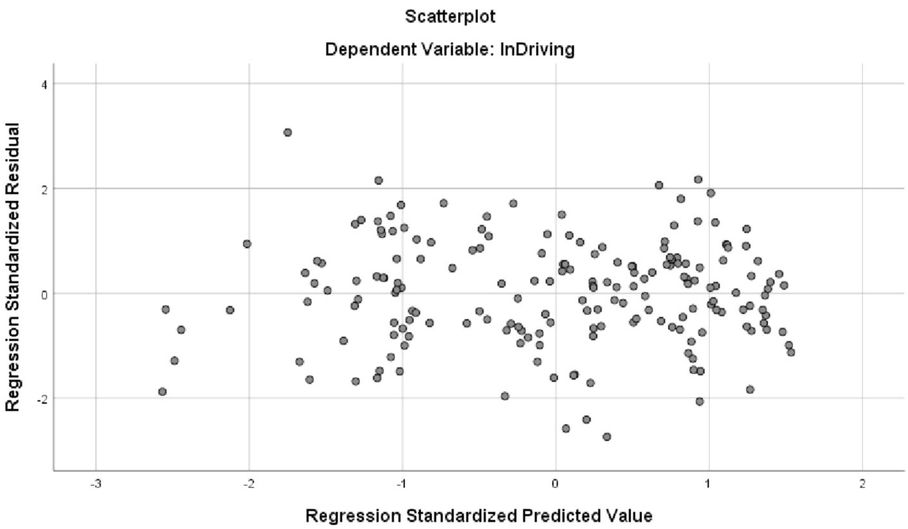

Fig. 5. Residual vs predicted values plot of the Model with lnDriving as the Dependent Variable in Sample 2.

when the Vac_{t-3} variable is in place, improving the model fit. In other words, compared with the Null model, vaccination played an important role in explaining the increase in mobility. We show the corresponding Null model for the Google data in Table 5.

4.3. Toda-Yamamoto test results

To estimate the augmented VAR model (Eq. (3)) for the Toda-Yamamoto test, the augmented Dicky-Fuller (ADF) test is used to examine the order of integration of the involved variables. From the results presented in Table 6, it can be seen that the $lnVac$ series reject the null hypothesis of a unit root at levels, and all variables reject the null hypothesis at the first differenced level. Furthermore, these results indicate that the $lnVac$ is a stationary series, while the $lnMobility$ and the $lnCovid$ are I(1) series. Thus, we determined that the maximal order of integration of all the variables is one.

Next, the Akaike Information Criterion (AIC) is used to determine the optimal lag order and cross-check it with the Schwarz information criterion (SC) and the Hannan-Quinn information criterion (HQ). As shown in Table 7, the lag structure results suggest that the optimal lag length for the VAR model is nine. Finally, the augmented VAR model is estimated with the maximal order of integration and the optimal lag length.

Table 4
Null model results with the mobility as the dependent variable for the two sample groups.

Dependent variable	Independent variable	Sample 1			Sample 2		
		Coef.	Std.Error	Std.Coef.	Coef.	Std.Error	Std.Coef.
lnDriving	Constant	3.478***	0.262		3.538***	0.111	
	lnCOVID	0.088***	0.029	0.299	0.117***	0.010	0.648
	lnTemp	−0.114***	0.044	−0.261	0.117***	0.038	0.167
	Adjusted R^2	0.219			0.454		
lnTransit	Constant	2.626***	0.380		2.347***	0.208	
	lnCOVID	0.141***	0.043	0.320	0.313**	0.018	0.783
	lnTemp	−0.196***	0.063	−0.298	0.019	0.070	0.012
	Adjusted R^2	0.272			0.611		
lnWalking	Constant	3.256***	0.255		2.599***	0.157	
	lnCOVID	0.065***	0.029	0.242	0.208***	0.014	0.729
	lnTemp	−0.078**	0.043	−0.193	0.182***	0.053	0.165
	Adjusted R^2	0.125			0.566		

Note: *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

Table 5
Null Model results with the mobility as the dependent variable for the two sample groups.

Dependent variable	Independent variable	Sample 1			Sample 2		
		Coef.	Std.Error	Std.Coef.	Coef.	Std.Error	Std.Coef.
lnR&R	Constant	2.907***	0.225		2.535***	0.139	
	lnCOVID	0.072***	0.025	0.291	0.174***	0.012	0.713
	lnTemp	−0.084**	0.037	−0.230	0.124***	0.047	0.131
	Adjusted R^2	0.187			0.531		
lnG&P	Constant	4.318***	0.104		4.202***	0.044	
	lnCOVID	0.004	0.012	0.036	0.049***	0.004	0.685
	lnTemp	−0.040**	0.017	−0.251	0.005	0.015	0.018
	Adjusted R^2	0.055			0.465		
lnParks	Constant	4.584***	0.217		4.251***	0.129	
	lnCOVID	−0.038	0.024	−0.173	−0.012	0.011	−0.071
	lnTemp	0.045	0.036	0.138	0.251***	0.044	0.390
	Adjusted R^2	0.054			0.145		
lnTS	Constant	3.278***	0.161		2.978***	0.104	
	lnCOVID	0.023	0.018	0.137	0.107***	0.009	0.644
	lnTemp	−0.063**	0.027	−0.253	0.084**	0.035	0.132
	Adjusted R^2	0.099			0.435		
lnWorkplaces	Constant	3.688***	0.289		3.363***	0.177	
	lnCOVID	0.025	0.032	0.085	0.083***	0.016	0.365
	lnTemp	−0.134***	0.048	−0.298	0.055	0.060	0.062
	Adjusted R^2	0.104			0.130		
lnResidential	Constant	4.784***	0.048		4.918***	0.034	
	lnCOVID	0.002	0.005	0.036	−0.023***	0.003	−0.487
	lnTemp	0.017**	0.008	0.232	−0.016***	0.012	−0.087
	Adjusted R^2	0.028			0.241		

Note: *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

Table 6
Unit root test results.

Variables	Intercept	Trend and intercept	None
lnMobility	−1.812	−1.552	2.437
lnVac	−3.243**	−3.891**	−0.076
lnCOVID	−1.866	−2.795	−0.147
ΔlnMobility	−13.866***	−13.950***	−7.115***
ΔlnVac	−3.910***	−2.685	−4.436***
ΔlnCOVID	−2.395	−2.409	−2.419**

Note: *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

Finally, the modified Wald test for the augmented VAR model is implemented to explore the causal relationships between the variables. Table 8 shows that the null hypothesis of non-causality from Vac and COVID to Mobility is rejected at the 1% level. In contrast, the null hypothesis of non-causality from Mobility to Vac and COVID is accepted at the 10% level, indicating a unidirectional causality running from Vac and COVID to Mobility.

Table 7
Lag structure based on AIC, SC and HQ.

Lags	Criterion		
	AIC	SC	HQ
0	2.917	2.955	2.932
1	−10.853	−10.700	−10.791
2	−11.650	−11.382	−11.543
3	−11.899	−11.517	−11.746
4	−11.861	−11.364	−11.662
5	−11.958	−11.346	−11.713
6	−12.261	−11.534	−11.970
7	−12.514	−11.672	−12.176
8	−12.717	−11.760	−12.334
9	−12.920*	−11.849*	−12.490*
10	−12.915	−11.730	−12.440
11	−12.876	−11.575	−12.354
12	−12.880	−11.465	−12.313

Note: * denote the optimal lag length chosen by the criterion.

Table 8
Wald test results.

Excluded	Chi-sq	p-Value
Dependent variable: lnMobility		
lnVac	27.32008***	0.0012
lnCOVID	43.38232***	0.0000
Dependent variable: lnVac		
lnMobility	15.35406	0.0817
lnCovid	14.69043	0.0998
Dependent variable: lnCovid		
lnMobility	15.43754	0.0796
lnVac	9.917031	0.3572

Note: *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

5. Conclusion

This work explored Covid-19 vaccinations' effects on increasing human mobility in London, UK. We aimed to provide evidence about vaccinations' role in London, UK's "return to normal" stages. Although we present some projections, forecasting human mobility in Covid-19-like pandemics was not our aim but to investigate the change in this mobility pattern when a massive vaccination program is implemented.

First, we find a positive correlation between vaccination and human mobility and human behaviour. The vaccination is positively associated with all types of mobility except for residential mobility during the lockdown ease stage (i.e., Sample 2), i.e., mobility for different modes of travel responds differently to vaccination. We observed a different mobility pattern between the first and third lockdowns. However, more importantly, in conjunction with the null model, they sustain our hypothesis that the vaccination programme positively affected mobility. Our observations suggest that public vaccination might reduce the public's perceived risk of infection, thus changing the travel mode choice.

Second, we find that the effect of temperature on mobility is significant during the period of lockdown ease. Interestingly, this effect varies by different types of points of interest. A relatively large effect occurs for parks, as it has a larger coefficient and standard coefficient for temperature. This suggests that, compared to the perceived risk of COVID infection, the weather is the major factor that to consider for people planning to go to parks during the mobility recovery.

Third, possible modal transfers from driving and walking to transit were observed, as both two ratios declined in the third lockdown and lockdown ease phases. Moreover, vaccination has a negative impact on these two ratios, suggesting that modal transfers from driving and walking to public transportation may be associated with public vaccination.

It is important to acknowledge that the reasons behind these mobility changes are not easy to point out. A possible factor is a change in the public's perceived risk of COVID infection caused by the increase in the vaccinated population, as mentioned by Serisier et al. [52]. Their study reported that participants were more likely to report non-household close contacts and use nonessential shops and services 14 days after their first dose of a COVID-19 vaccine than they were before vaccination in England and Wales. The changing mobility trend may also be caused by COVID fatigue [23]. Furthermore, the local policy variable strongly affects mobility in different lockdown stages. Although we further examined the relationship between the variables by applying a causality analysis method and the single-directional causality running from vaccination and COVID cases to total mobility is confirmed, we must not attribute the change in mobility solely to a large number of people vaccinated.

Although we found a correlation between multiple types of mobility and vaccination in the London area using regression methods and have proved the "causal relationship" between mobility and vaccination using a causality test, we need to note that the relationship between variables cannot be proven to be a true causal relationship, because the essential of Granger causality is that the previous changes in one variable can effectively predict another variable. This is also a limitation of our research. More empirical studies in different regions and geographical levels must be combined to demonstrate the causal relationship between mobility and vaccination, which requires further research. All these different factors are absent in our model, limiting its explanatory capabilities. What is needed is to keep presenting further evidence which needs to be taken forward to understand how epidemiological processes affect our daily lives and mobility in cities.

Our findings provide some insights into how vaccination programs affect people's behaviour and movement, suggesting that people feel more confident and safer moving around and resume their normal activities once the population is vaccinated. This information could encourage more people to vaccinate and plan for increased city mobility. Understanding the relationship between vaccination and mobility can help public health authorities, and policymakers make informed decisions about easing or tightening restrictions and implementing measures to control the spread of the virus.

CRediT authorship contribution statement

Honghan BEI conceived and designed the experiments; analyzed and interpreted the data; wrote the paper.

Peiyan Lib conceived and designed the experiments;performed the experiments; analyzed and interpreted the data; wrote the paper.

Zhi Caib conceived and designed the experiments;performed the experiments; analyzed and interpreted the data; wrote the paper.

Roberto Murcio conceived and designed the experiments; analyzed and interpreted the data; wrote the paper.

Additional information

No additional information is available for this paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Not Applicable. All the data used in this work is from open sources cited in the text.

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Appendix A. General trends by activity

To further test our model's performance, we compared their general trends with the figures obtained from Google data. Fig. A.1 depicts the Google data (by activity) for March 2021, i.e., the first lockdown. From the working panel, we can observe that the actual walking mobility fluctuates strongly and increases gradually. From the retail panel, we can find that the actual data has four major peaks and fluctuate strongly. Finally, in the transit station panel, the actual data increases significantly and has a weak fluctuation. For all three panels mentioned above, their model results follow the trend of actual data and can simulate the fluctuations to a certain extent.

Now, Fig. A.2 (July 2021) gives us an idea of what happened at the end of the third lockdown, ease phase. We can observe at the working panel that the actual walking mobility has four peaks and get the maximum at the end of the month. The retail panel shows that the actual data fluctuate strongly at a certain level. The actual data in the transit station panel also showed four peaks and got the maximum at the end of the month. For all three panels mentioned above, their model results only follow the trend of actual data, and it cannot simulate the fluctuations of actual data.

Appendix B. Diagnostic test

Figs. B.1, B.2, B.3, and B.4 show the diagnostic plots of the regression models. Scattered points tend to form a cluster in the residuals vs predicted values plots on both sides. The predicted values' distribution is the cause of this and does not indicate a clear pattern in the distribution of residuals relative to the predicted values. Therefore, when determining the homogeneity of variance, we consider the distribution of scattered points within the cluster.

The residual of the models using sample 2 is closer to the Normal distribution, and there is no obvious heteroscedasticity, which indicates that the lockdown period model is more reliable and unbiased than the other model. In addition, the residual distribution of the model with the mobility of working areas and residential areas as the dependent variable is not close to the Normal distribution. There is an obvious heteroscedasticity phenomenon, mainly because the cyclical changes of these two types of mobility are particularly obvious within a week. Our model does not consider the impact of controlling working days and weekends.

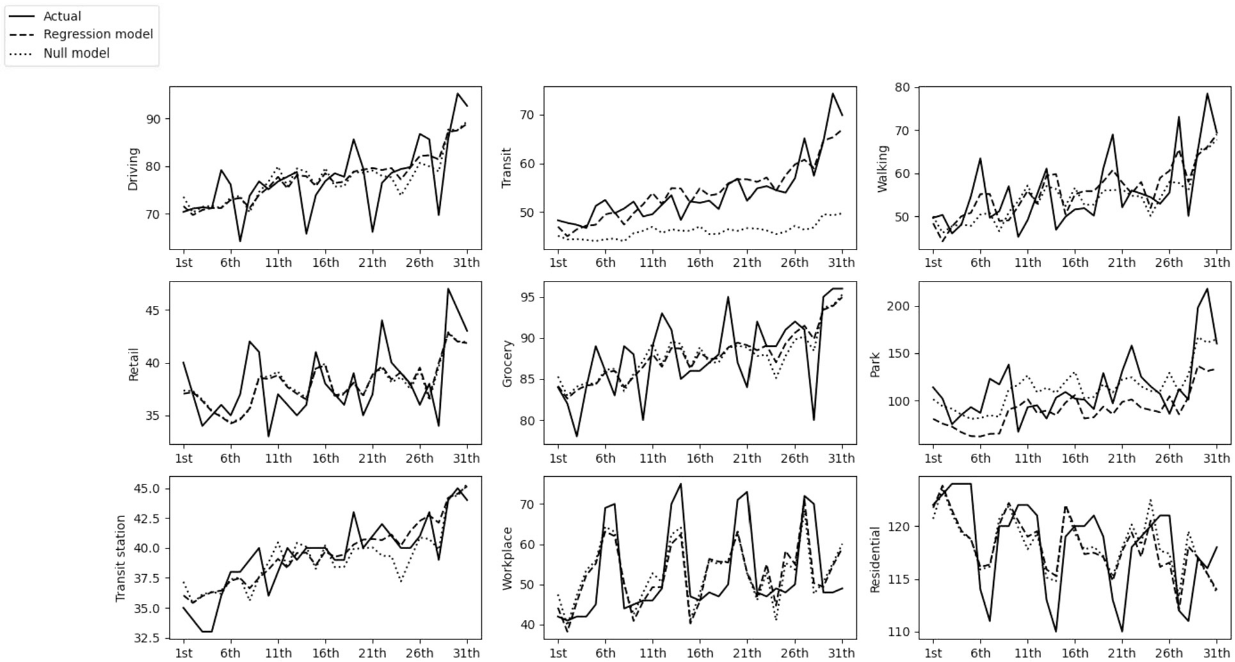

Fig. A.1. March model.

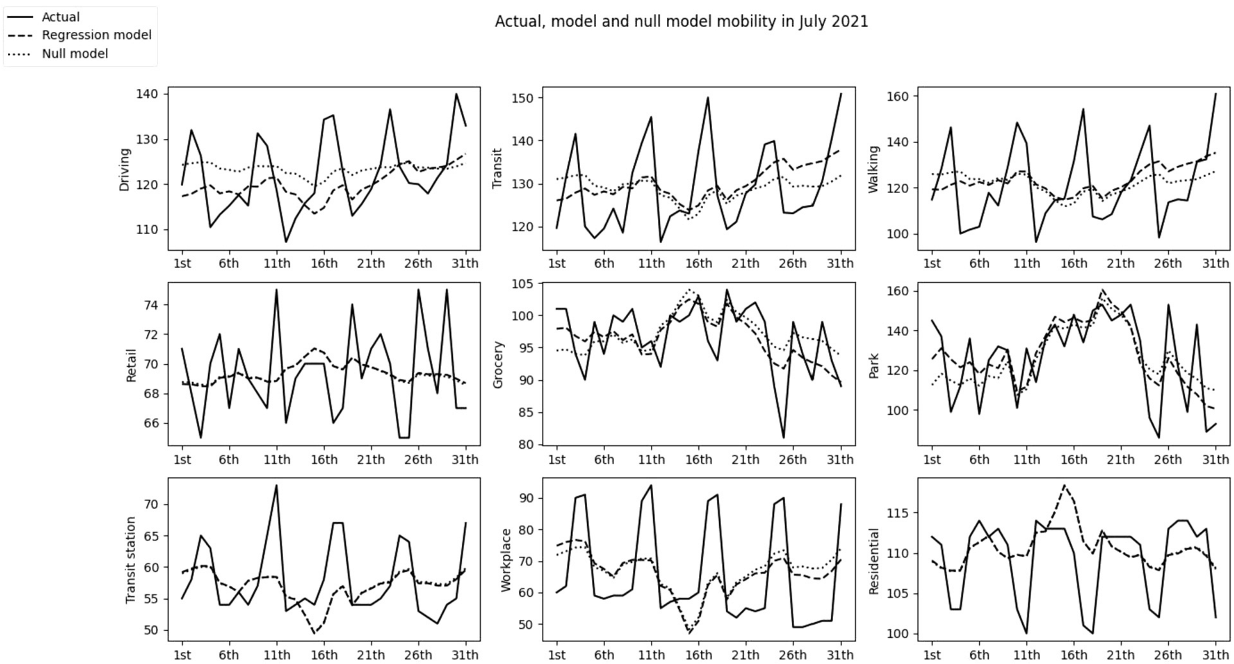

Fig. A.2. July model.

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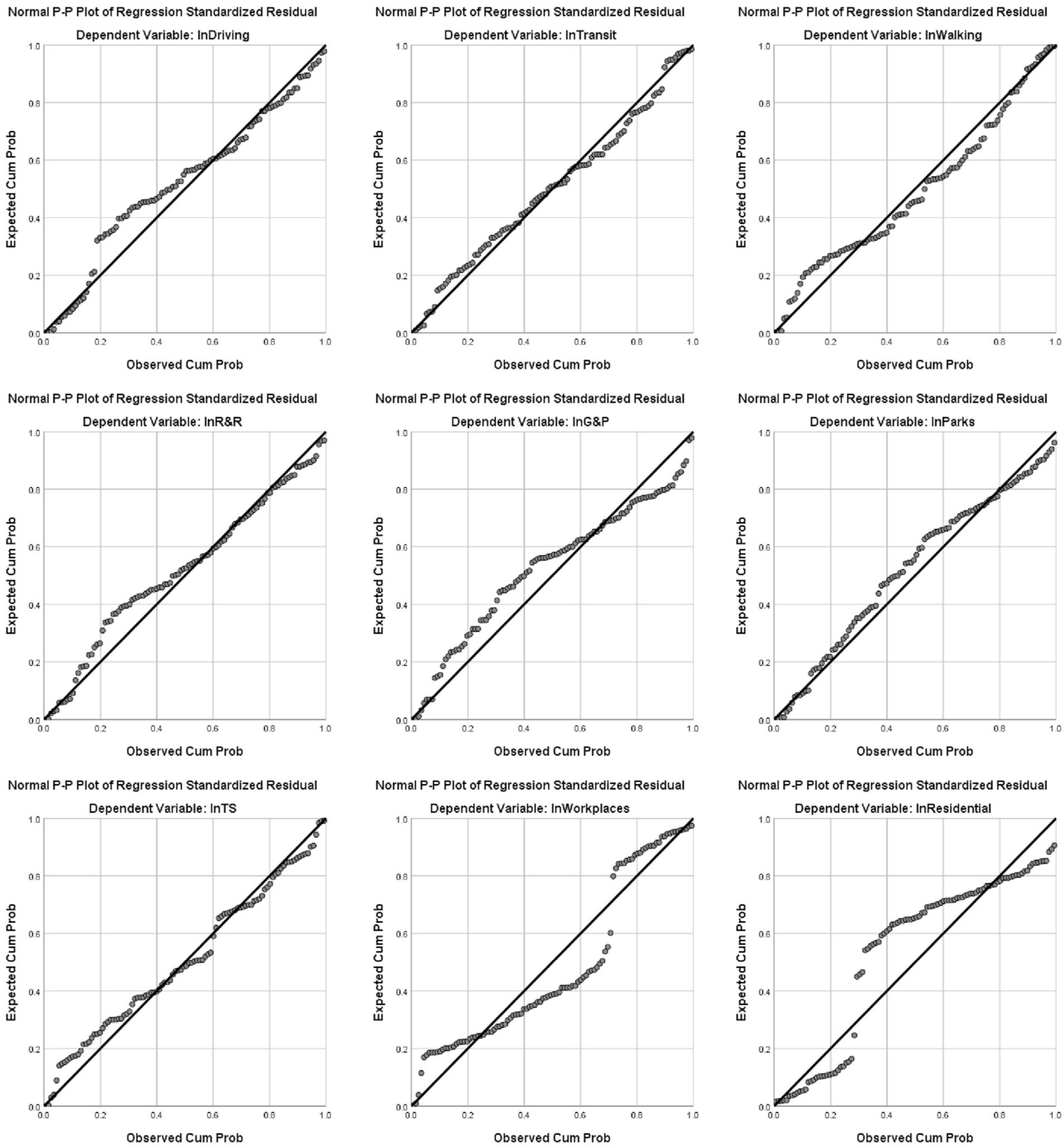

Fig. B.1. Normal probability plots for the models using sample 1.

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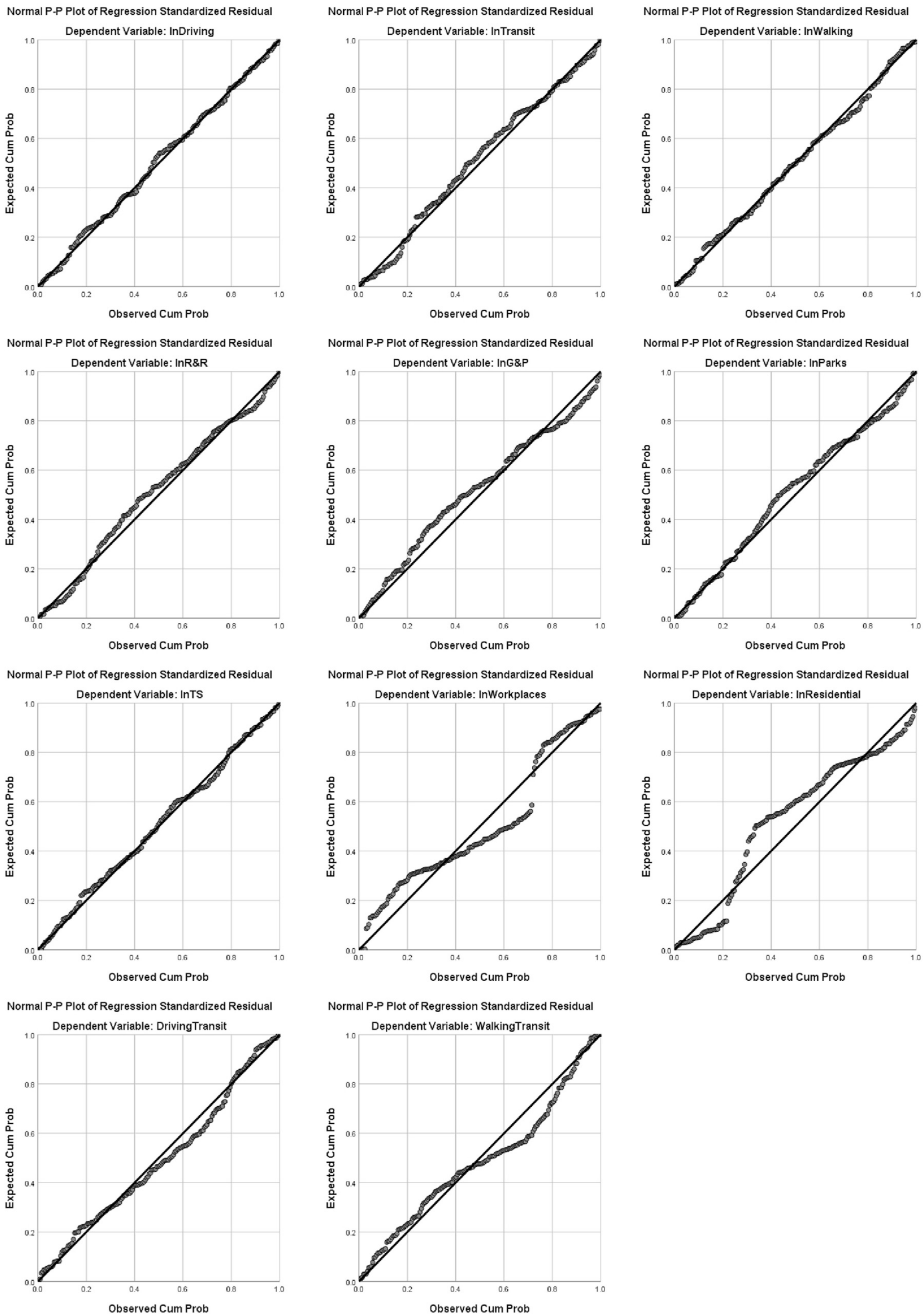

Fig. B.2. Normal probability plots for the models using sample 2.

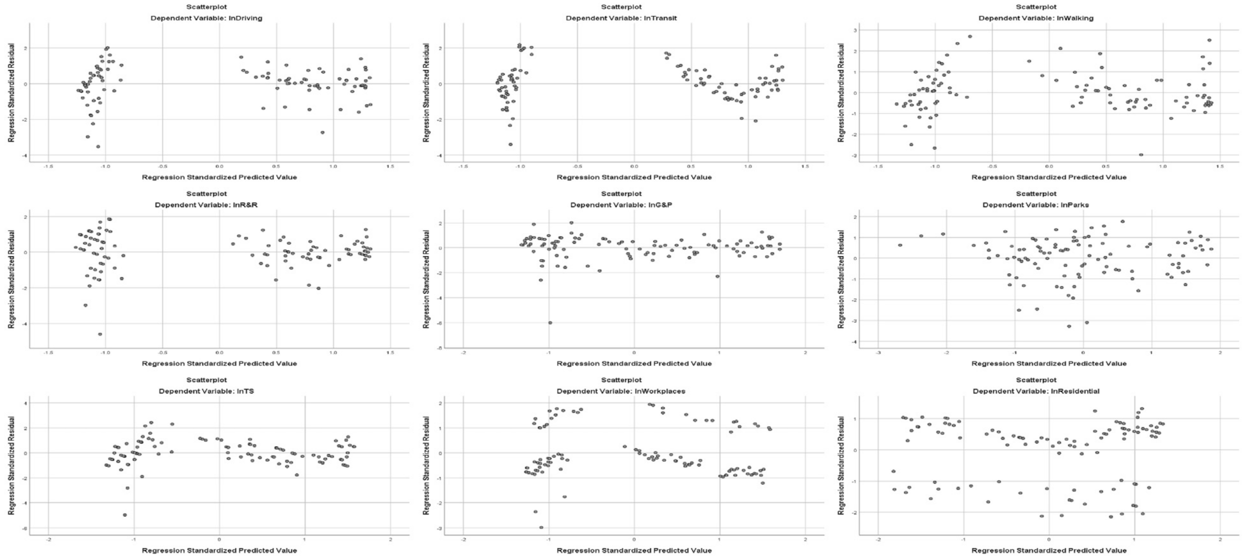

Fig. B.3. Residual vs predicted values plots for the models using sample 1.

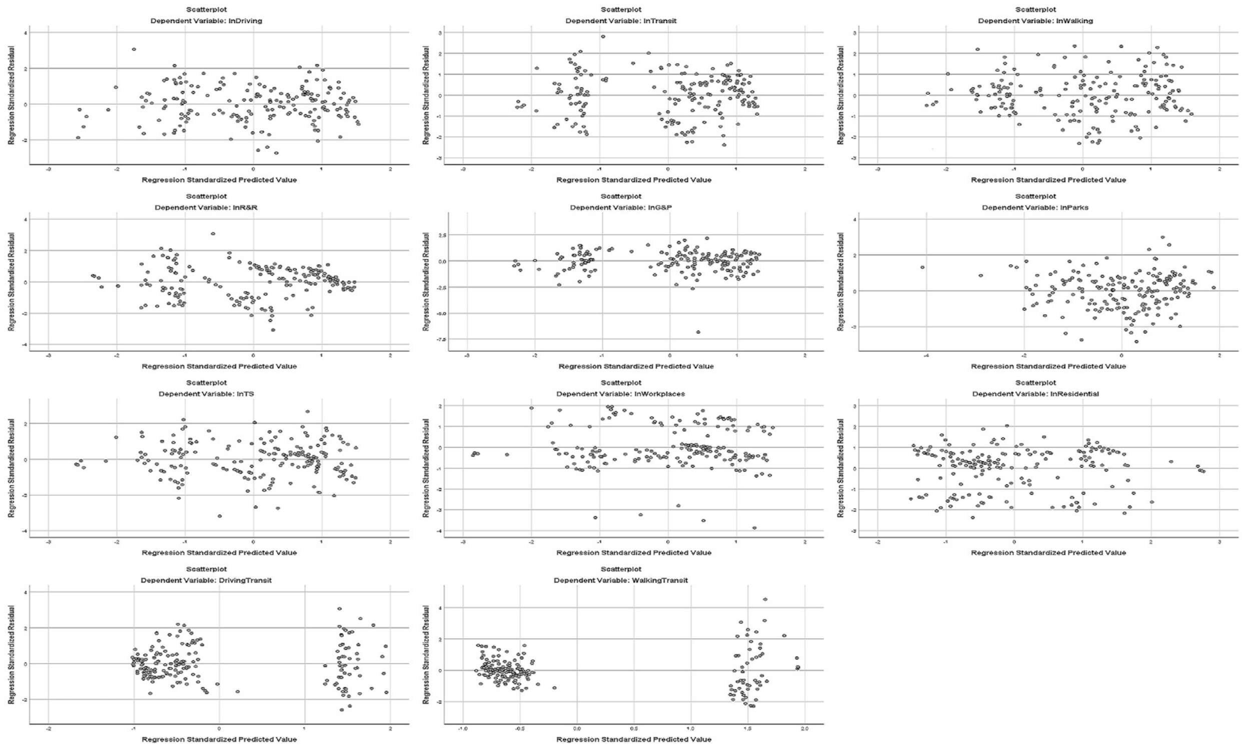

Fig. B.4. Residual vs predicted values plots for the models using sample 2.

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