The impact of Weather on Train Operator Performance in England, Scotland and Wales

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Abstract

This study examines the effect different weather conditions have on key performance metrics for 21 train operators running in England, Wales and Scotland. With a global climate emergency and weather becoming more extreme and unpredictable, it is important to understand how this will affect the railways so mitigation efforts can be focussed in protecting against weather conditions which have the greatest impact on train operator performance. Understanding how weather affects the performance of train operators is important for focussing efforts to maintain the competitiveness of the railway and its economic viability. This study analyses how temperature, rainfall, snow, windspeed, and the seasonal impact of autumnal leaves on railway track affect two different dependent variables: the number of delay minutes and number of cancelled trains recorded for each train operator. I have used data from April 2011 to March 2020 for delay minutes and April 2014 to March 2020 for cancelled trains in which 13 four-week periods are reported for each financial year. I have matched the appropriate weather conditions onto each four-week period to construct a panel dataset in which the impact of weather on delay and cancellations can be analysed. I have used random effect modelling to analyse the data, as, indicated by the Hausman test, it was more appropriate than a fixed effects model. Analysis shows that hot and dry weather conditions have a significant affect on delay minutes, with high temperature increasing delay by 4,694 minutes and low rainfall increasing delay by 4,810 minutes, which is an increase of 9.2% and 9.5% respectively when compared to mean delay minutes in a four-week period. Heavy rain, cold temperatures and high windspeed increase delay minutes but by a smaller amount than hot and dry weather conditions. For the number of cancelled trains, fewer weather conditions were found to be significant in affecting the number of cancelled trains. Temperature was the only variable which was shown to increase the number of trains cancelled, with temperatures below 0°C and above 21°C increasing the number of cancelled trains by 269 and 203 trains respectively. This represents an increase of 38.7% and 29.3%, when compared to the mean number of trains cancelled in a four-week period. The month of November is significant in all models I have tested for both dependent variables, confirming that leaves on the track, which is prevalent in the autumn months leads to more delay. The key policy implications from my analysis are that it would be most beneficial to protect against hot and dry weather conditions and the seasonal impact of leaves on the track during the autumnal months, specifically November.

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) states in its latest report that climate change is "already affecting many weather and climate extremes in every region across the globe" (IPCC, 2023). The global surface temperature is 1.1°C above the temperature in 1900 (IPCC, 2023). This is apparent in the UK alone with highest temperature on record seen in July 2022, with England reaching 40.3°C (Met Office, 2022).

The railways are a crucial mode of transportation, with 31,209km of track covering Great Britain (Office of Rail and Road, 2022), and will face their own unique risks when it comes to climate change, with impacts being likely more impactful due to the knock on effects delays for one train has for other trains on the network, and the unique safety considerations needed to run trains on the network (Palin et al, 2021). More extreme temperatures, and higher rainfall and windspeeds, leading to flooding and storm damage, will all affect rail infrastructure. Heavy rainfall can lead to embankment instability (Dawson et al, 2018) and track flooding (Palin et al, 2021). In 2018, 2,400km of the UK rail network was at risk of flooding (Dawson et al, 2018). High temperatures are also costly for the railways with the 2003 heatwave costing £2.5 million to repair the rail infrastructure due to rail buckling (Dawson et al, 2018).

The impacts of weather conditions on railway infrastructure have a direct impact on train operators in the form of delayed or cancelled train services. Network Rail reports in its third adaptation report, which outlines their latest plans for climate adaptation, that 322,000 delay events have been caused by weather, with the caveat that this is a conservative estimate (Network Rail, 2021). This has an effect on passenger satisfaction, which is important to maintain loyalty towards a service (Keaveney, 1995), and so maintaining competitiveness for the railways. A study by Monsuur et al found that passengers react negatively to delays which are over 30 minutes and this is exacerbated when trains are cancelled (Monsuur et al, 2021). The opportunity cost of using rail travel may become higher than using other modes of transport if repeated delays or cancellations are incurred. Passengers who do not arrive at their destination on time may have missed important commitments. If consistent delay is experienced, passengers may view the service as unreliable and opt to use other substitutable modes of transport, such as driving. Negative passenger reactions can also damage the railway company's reputation, especially in the age of social media, so customers who may be considering using the service may choose a different mode of transport, regardless of whether they have experienced delay themselves or not. There is a direct economic cost to delay, with Xia et al estimating that 3 minutes of delay for one passenger costs 2.5 euros (Xia et al, 2013). Delays and an unreliable train service can affect both the economic viability of the service and the productivity of those passengers using the service, which has a knock-on effect to the wider economy. The Department for Transport estimates in their Transport analysis guidance (TAG) Databook that the perceived cost per hour of railway travel is £32.71 in 2023 prices, allowing for the inference that the cost of train delays for a passenger in the UK is £32.71 per hour (Department for Transport, 2023).

My research question examines how different weather conditions impact the performance of train operators in the UK. This study assesses the impact certain weather conditions have on the amount of delay minutes and number of cancelled trains attributed to train operators each month, aiming to inform where funding should be spent and which weather types to prioritise mitigating against. This analysis will be useful to identify the weather conditions that will have the most impact, to inform where risk mitigation efforts should be prioritised, in an industry where limited funding is available (Brazil et al, 2017). I will use the software Stata to perform regression analysis to calculate the marginal impact of different types of weather, as informed by previous literature.

This study focusses on train operators who run services in England, Wales and Scotland. Train operators tend to run in specific geographical areas, so they will be subject to different weather conditions. For example, operators who run in Scotland and the North of England will be subject to colder weather conditions than those who run in the South of England. I will compare how different weather conditions which are experienced in different areas of Great Britain affect the performance of train operators. This study provides novel evidence on the relationship between performance and weather since it uses an annual time frame which has not been covered in other studies. The study also uses panel data on a wide area of track whereas other studies focus on one smaller section of railway. To my knowledge, a study like this has not been done for England, Scotland and Wales.

2. Literature review

A number of studies directly explore the effect of weather on train operator performance. These studies have provided useful insight into which weather variables I should be focussing on. However, the studies that do explore this topic use either a small section of railway or data from only one year. My literature review is split into two parts: variable selection and data analysis approaches. I have used the studies which are most similar to my dissertation topic to inform the selection of the weather variables used. I have then explored wider approaches to modelling panel data to understand how best to model the data I am using in my dissertation.

2.1 Variable selection

The impact of weather on train operator performance has been examined directly in a number of studies, using a range of approaches to model performance. Some studies have used measures of punctuality, defined as trains which have delay under three (Xia et al, 2013) or four (Zakeri and Olsson, 2018) minutes and the number of cancelled trains (Xia et al, 2013). Other studies compared published train schedules with actual train times (Brazil et al, 2017 and Nagy and Csiszar, 2015). These measures all focus on the percentage of trains which are on time whereas I have chosen to explore the amount of delay minutes recorded by each train operator and the number of trains each operator has cancelled each month. I have chosen this due to data availability based on what is reported by the Office of Rail and Road and available in the public domain.

Several weather variables have been shown to be significant when it comes to their effect on train performance. A study by Xia et al, based on data in the Netherlands, found that snow, extreme within day temperature variation, high temperatures, rain, and wind all affect punctuality and the number of cancelled trains (Xia et al, 2013). This study also includes monthly dummy variables to include the effect of autumn and the increased number of leaves on the track in those months. Brazil et al found that rain and the month of November (representing the impact of leaves on the track) were significant factors affecting railway punctuality, using data from Dublin (2017). This study also stated that their analysis was limited by not controlling for passenger numbers (Brazil et al, 2017). A study on the Nordland line in Norway, concluded that snow depth had the main effect on punctuality of trains (Zakeri and Olsson, 2018). Nagy and Csiszar's (2015) study in Hungary found that extreme cold, snow and extremely hot and dry weather conditions caused trains to be delayed. Chen and Wang (2019) show that heavy rain, thunderstorms and snow cause disruptions to high-speed rail.

The inclusion of weather variables has varied between studies, particularly for temperature. The studies above have used different approached to including temperature in their analysis and have found varying results on which temperatures are significant in causing delay. The table below summarises how different studies have defined hot and cold weather.

Table 1: Temperatures which have been shown to be significant in causing delay

Authors	Temperature at which delay is caused	
	Hot weather	Cold Weather
Xia et al, 2013	Above 23°C	Below -3°C
Brazil et al, 2017	Above 27°C	Below 2°C
Nagy and Csiszar, 2015	Above 30°C	Below 3°C
Mesbah, Lin & Currie, 2015	Uses how far from mean weather data is, mean weather is defined as 15°C	

I will be testing the effect of temperature, wind, rain, snow and dummy variables for autumnal months in my analysis. I will explore the different approaches to including temperature and to assess which is most appropriate for my dataset, since temperatures in Great Britain are less extreme than in many of the areas that have been studied.

2.2 Approaches to modelling

Most studies which look at the impact of weather on railway performance use linear regression models in their analysis. Xia et al uses a time series dataset of daily observations, over an eight-year period and analyses the data using a standard linear regression model (Xia et al, 2013). Brazil et al uses simple multilinear regression models to analyse a panel dataset of daily observations from 2013. They used Akaike's Information Criterion (AIC) to decide which variables in include in the regressions and reports the ANOVA values associated with each model (Brazil et al, 2017). Zakeri and Olsson also use linear regression analysis to analyse passenger trains from 2007 to 2016. To avoid multicollinearity, they have only included variables with a correlation coefficient below 0.8 and a Variance Inflation Factor (VIF) that is below 5 (Zakeri and Olsson, 2018). Guo, Wilson and Rahbee estimate 12 Ordinary Least Squares (OLS) models which differ in specifications to assess how weather affects both rail and bus usage in Chicago (2007). They decided to use OLS as it is a simple model which they could apply to different scenarios.

The previously mentioned studies use data analysis methods which are mostly suitable for timeseries or cross-sectional data. The modelling techniques are therefore not helpful for analysing the dataset I am using, since I will be using a panel dataset, with observations for 21 train operators over nine years. Analysis of this type of data comes with a different set of potential issues and the relationship observed is likely not to be explained sufficiently by using linear regression analysis. Pooled OLS models can be used to model panel data, but other modelling techniques can model panel data more accurately since pooled OLS would not model train operators as different entities and instead would combine all the datapoints together. I have therefore explored other approaches to analysing panel datasets.

Panel data is commonly analysed using fixed or random effects models. Both fixed and random effects account for unobserved differences between the entities being sampled but by using different approaches (Bartels, 2009). Cheng and Zhao (2020) have used a random effects model, after the Hausman test indicated it was preferred over random effects to model poverty rates in different regions in China. While this study is not related to transport, the dataset used is of a comparable structure to my analysis. I will use the Hausman test to assess whether fixed or random effects are most appropriate for my dataset.

3. Methodology

The hypothesis I will be testing is that months in which there are increased instances of inclement weather will have higher numbers of delay minutes and cancelled trains. I will be using historic monthly data from April 2011 to March 2020 to test how weather has impacted delay minutes recorded by train operators and from April 2014 to March 2020 to test the impact on the number of trains cancelled.

3.1 Data

The data sample consists of performance information for 21 passenger train operating companies for each four-week rail period. To measure train operator performance, I have used two metrics which are reported by the Office of Rail and Road (ORR). ORR are the economic and safety regulator for the railways. ORR is also the primary producer of Official Statistics for rail. The majority of the statistics they publish are designated as National Statistics by the Office for Statistics Regulation (OSR) (Office of Rail and Road, no date). The ORR data portal is a way of accessing and downloading rail statistics which is accessible in the public domain. I have used two variables from the passenger rail performance section of the data portal for my analysis: total delay minutes[1] and the number of cancelled trains[2]. For delay minutes, this sample is over nine years, from April 2011 to March 2020. This is a panel dataset consisting of 2,457 observations. I have excluded the period after March 2020 due to Covid-19 since, due to a reduced number of services, train operator performance was not representative. For the number of cancelled trains, I have used a shorter timeframe due to data availability, with six years from April 2014 to March 2020. This panel dataset provides 1,638 observations.

While other studies have used punctuality (percentage of trains which are on time) as a measure of delay (Xia et al, 2013 and Zakeri and Olsson, 2018), I have chosen to look at trains which were not on time as they provided the greatest number of observations and allow me to capture the effect of weather on both late trains and trains which are cancelled. The delay minutes dataset is disaggregated into causes and one cause recorded is 'severe weather, autumn and structures' (Office of Rail and Road, no date). Data attributed to severe weather only accounts for 7% of total delay minutes recorded by operators so I have chosen to look at all delay minutes to capture all weather effects, even those which may not have been categorised as due to weather at the time. This was also done by Xia et al (2013), with the rationale that delay cannot be attributed to weather with certainty. I have used weather data recorded by the Met Office (no date), which is accessed through their website under UK and regional series as part of their climate research. I have also used data from The Department for Business, Energy and Industrial Strategy (BEIS), which is accessed through the GOV.UK website (GOV.UK, 2023) and data recorded in the CEDA Archive (2022). These are all reliable sources of data, with the CEDA archive reporting data collected by the MET Office and BEIS reporting aggregates of data also collected by the MET office. The weather variables I will be testing are outlined in the table below.

[1] Table 3184
[2] Table 3124

Table 2: Description of weather variables and their sources

Weather variable examined	Description	Variable type	Source
Maximum Temperature (°C)	Average daily maximum temperature over a given month.	Continuous	MET office
Minimum Temperature (°C)	Average daily minimum temperature over a given month.	Continuous	MET office
Mean Temperature (°C)	Average of daily mean temperature over a given month.	Continuous	MET office
Rainfall	Total precipitation in a month, measured in mm.	Continuous	MET office
Rain days	Number of days in a month where rainfall was greater than 1mm.	Continuous	MET office
Days of snow lying	Number of days in a month where greater than 50% of the ground was covered by snow.	Continuous	CEDA Archive
Average windspeed	Average windspeed in a given month, measured in knots, over the whole of the UK.	Continuous	BEIS

To control for differences between train operators[3] I have included proxies for passenger demand as recommended by Brazil et al (2017) in the form passenger kilometres[4] and number of passenger journeys[5]. The rationale is that trains which travel either further or more frequently, with a greater number of passengers are likely to have higher levels of delay in general. Train operators which travel further distances will have a greater number of delay minutes attributed to them. Operators which carry more passengers, are likely to have more delay minutes, as there is more opportunity for delay to be caused by passengers boarding the train. I have also controlled for complexity of the routes travelled by different train operators by using the number of stations[6] the operator manages as an approximation for the number of stations they stop at. Stopping at more stations, means more opportunity for there to be delay. These variables were all obtained from ORR's data portal. These variables are reported annually for each operator.

3.2 Data mapping

Data is available for 23 train operators from the ORR's data portal. I have excluded two of these operators as they did not have the full set of observations which means I would have an unbalanced panel dataset if I included them, which adds additional complexity when modelling. ORR reports railway performance data in 13 four-week rail periods. The railway period dates are reported on the ORR data portal[7]. I have used these 13 rail periods and matched

[3] It would be preferable to control for differences in track condition on different parts of the railway infrastructure, however the data was not available publicly at a suitable level of granularity for this analysis.
[4] Available from the ORR data portal under Passenger rail usage, table 1233.
[5] Available from the ORR data portal under Passenger rail usage, table 1223.
[6] Available from the ORR data portal under TOC key statistics, table 2243.
[7] Available from the ORR data portal under Railway period dates (CP1 to CP6).

the most relevant weather conditions to each period based on which month makes up the majority of the rail period. The data is mapped according to the table below.

Table 3: Rail periods and their corresponding month

Rail Period	Month
Period 1	April
Period 2	May
Period 3	June
Period 4	July
Period 5	August
Period 6	September
Period 7	September
Period 8	October
Period 9	November
Period 10	December
Period 11	January
Period 12	February
Period 13	March

The MET office reports data split into eight districts, which cover different parts of the UK[8]. For the data I obtained directly from the MET office, I have mapped the routes each train operator takes to an area of the UK and then used the weather reported for that area.

BEIS reports average windspeed for the whole of the UK for each month, I have therefore mapped each month of this data onto each train operator. Since the dataset reports average windspeed and the UK is not usually subject to extreme wind speed in the way other countries are, it is a reasonable assumption to use this data for all train operators. This still captures the monthly variation of wind in each month, allowing the change to be captured in the analysis but the impact of different wind speeds on different operators is not included, lowering the data quality in this area.

The CEDA archive reports monthly data in 16 regions, capturing the whole of the UK. I have mapped the regions I assigned to each train operator for the MET office data to the relevant region from the CEDA data. This has involved aggregating some of the CEDA data so that the regions are comparable. The ORR data on passenger km, passenger journeys and managed stations is reported annually and quarterly. I have used the annual data and averaged it to four-week periodic numbers for passenger journeys and passenger km. This assumption loses the exact journeys completed each month for train operators and loses the influx in demand possibly seen around Christmas time for example, which means the impact of higher demand on delay will not be completely captured by the analysis. For the number of managed stations, I have reported the yearly amount for each railway period, capturing any annal changes in the number of stations. The descriptive statistics for each variable included in my analysis are shown in the table below.

[8] A map showing these districts is available on the Met Office website under UK climate districts map.

Table 4: Descriptive statistics

Variable	Max	Min	Mean	St.dev
Total delay minutes	359,467	935	50872	48501
Number of trains cancelled	11,392	0	694.44	1,045.90
Max Temperature	26.10	4.20	14.20	4.98
Min Temperature	14.00	-3.20	6.23	3.83
Mean Temperature	19.90	1.30	10.30	4.35
Rainfall	334.70	2.50	79.84	43.87
Rain Days	28.10	0.60	11.69	4.62
Windspeed	14.05	5.48	8.68	1.60
Snow	12.17	0.00	0.63	1.51
Passenger journeys	26.84	0.05	5.94	6.15
Passenger km	0.72	0.01	0.23	0.18
Managed stations	478	0	119	126

3.3 Temperature variables

As reported in the literature review, the approach to temperature in analysis varies from study to study. I explored how different approaches affected my results and which gave the most significant and intuitive outputs. The raw data I collected on temperature was mean, minimum, and maximum temperature for each month. Maximum, minimum, and mean temperature is highly correlated, as shown in Table 5 below, so all three variables cannot be included in the analysis as there will be issues with multicollinearity.

The data recorded is the maximum and minimum average temperature so does not capture what the actual hottest temperature or coldest temperature was in each month, hence why my dataset does not show temperatures above 26°C or below - 3°C despite these temperatures being reached in the UK in this period. The MET Office reports that temperatures reached 38.7°C in 2019 (Met Office, 2022) but this is not reflected in the data. Therefore, the benefit of including the maximum and minimum temperature variables on their own is limited as any extreme temperatures on a given day are missed.

As informed by the study by Xia et al (2013), I tested two additional temperature variables. Xia et al found that extreme within day variations were significant so I created a variable which captures the variation between maximum and minimum temperature for each month to assess if these differences affected delay. Xia et al also included a 'relevant temperature' for which if the average temperature was below 12°C, the minimum temperature on that day was used and if the average temperature was above 14°C, the maximum temperature was used. I created a variable using this method to test in my analysis.

I also tested the inclusion of dummy variables for temperature above 23°C and below 2°C, as informed by Table 1 in my literature review. I explored a dummy variable which capture the 5th percentile of cold weather and the 95th percentile of hot weather to assess how extreme temperatures for my dataset affected performance. This is informed by the maximum and minimum values included in my dataset and the way in which this data was distributed. These values were above 21°C and below 0°C.

Table 5: Correlation coefficients for temperature

	Max Temp	Min Temp	Mean Temp	Temp difference	Temp <2°C	Temp <0°C	Temp > 23°C	Temp > 25°C	Relevant temperature
Max Temp	**1**								
Min Temp	**0.9442**	**1**							
Mean Temp	**0.9937**	**0.9652**	**1**						
Temp difference	0.7331	0.468	0.6728	**1**					
Temp <2°C	-0.57	-0.6061	-0.5768	-0.2778	**1**				
Temp <0°C	-0.2639	-0.3272	-0.269	-0.0324	0.4165	**1**			
Temp > 23°C	0.2696	0.2122	0.2518	0.285	-0.0565	-0.0235	**1**		
Temp > 21°C	0.453	0.4076	0.4422	0.3737	-0.1142	-0.0476	0.4942	**1**	
Relevant temperature	0.9027	0.9202	0.918	0.5216	-0.4533	-0.2274	0.2799	0.1398	**1**

3.4 The impact on delay minutes and cancelled trains

3.4.1 Variable selection

I found that using the mean temperature, difference between maximum and minimum temperature and dummies for temperature below 0°C and dummy for temperature above 21°C was best for modelling the relationship between temperature and performance as they produced the most significant results in my preliminary modelling. I chose to include windspeed and rainfall variables without manipulation of the data to capture how a unit change in these variables would impact performance. I also chose to assess what the impact of extremes of these types of weather would be on performance and so created dummy variables for the top 95% percentile and bottom 5% percentile. For windspeed this was above 12 knots and below 6 knots in a month. For rainfall this was above 160mm and below 23mm of rain in a month. It did not seem appropriate to model these extremes for snow as the variable used for snow measures the number of days where at least 50% of the ground is covered in snow and does not differentiate between different volumes of snow in these periods. I included the control variables I had identified in each model, which was passenger km, passenger journeys and number of managed stations. I also included periodic dummies to capture the effect of autumn and the 21 increased number of leaves on the track (Xia et al, 2013). I explored whether it was more appropriate to include a time trend or yearly dummies in my analysis.

3.4.2 Model specification

I tested the correlation coefficients of all the variables I was intending to include in my analysis, with a view to removing any variables where the correlation coefficient was above 0.8 to avoid the presence of multicollinearity in the regression as independent variables need to be independent of each or this can cause issues with the results. As shown by Table 9 and 10 in Annex 1, the correlation coefficients for all variables and their relationships with both delay minutes and cancelled trains were all below the cut-off point, so no variables needed to be removed.

To assess what the most appropriate modelling technique would be, I tried modelling my dataset using pooled ordinary least squares (OLS) and fixed and random effects generalised least squares models. The pooled OLS model provided results for some variables which were not representative of what would happen in real life, for example the model showed rainfall as a factor in reducing delay, which is contradicted by all the relevant literature. I then used the Hausman test to assess whether fixed or random effects would be most appropriate. The Stata Hausman tests to see if there is a systematic difference between the two models, if the null hypothesis is rejected this suggests the fixed effects model should be used.

4. Results

4.1 The impact of weather on total delay minutes

Firstly, I chose to model the effect different weather variables had on delay, without dummies for weather extremes. The Hausman test for this model gave a test statistic of 0.3442, which meant I could not reject the null hypothesis meaning a random effects model should be used.

Equation 1 shows the equation used to model the relationship

$$\begin{aligned} DM = {} & \beta_1 MT + \beta_2 TD + \beta_5 R + \beta_6 S + \beta_7 W + \beta_8 PD1 + \beta_9 PD2 + \beta_{10} PD3 + \beta_{11} PD4 \\ & + \beta_{12} PD5 + \beta_{13} PD6 + \beta_{14} PD7 + \beta_{15} PD8 + \beta_{16} PD9 + \beta_{17} PD10 \\ & + \beta_{18} PD11 + \beta_{19} PD12 + \beta_{20} T + \beta_{21} PK + \beta_{22} PJ + \beta_{23} MS + \alpha + (\mu + \epsilon) \end{aligned}$$

Where DM is total delay minutes, MT is mean temperature, TD is temperature difference, R is rainfall, S is snow, W is windspeed, PD1 to PD12 refer to period dummies for periods 1 to 12, T is the time trend, PK is passenger km, PJ is passenger journeys, MS is managed stations, α is the unit specific effects and (μ + ϵ) is a composite error term.

It is important to test for econometric issues which may affect the validity and interpretation of my results. One issue that can arise with panel data is heteroskedasticity, which means that there is not constant variance of residuals, which can lead to issues with the results output by the regression and makes the model likely to misreport the significance of variables. I used the Breusch-Pagan Lagrangian multiplier test to test for heteroskedasticity in the random effects model. The test statistic was 0, which means the null hypothesis of homoskedasticity is rejected and there is strong evidence of heteroskedasticity in my model.

Another issue that can affect panel data models is autocorrelation. If autocorrelation is present, this means that the delay seen by a train operator in one period has an effect on the delay seen in the period after it. This can lead to relationships being incorrectly represented in the regression analysis. To test for autocorrelation, I used the Wooldridge test for autocorrelation in which the null hypothesis is that there is no first-order autocorrelation. The test statistic reported was 0.0004 which means I can reject the null hypothesis, so autocorrelation is present in my model. The robust standard errors option in Stata can be used to produce consistent estimations when heteroskedasticity and autocorrelation are present. I decided to use robust standard errors in my model to adjust the standard errors for the impact of autocorrelation and heteroscedasticity so I could make accurate inferences from my regression output.

The results from the most relevant variables in this regression are outlined below in Table 1, using a random effect generalised least squares model, with robust standard errors for Models 1 and 2.

Table 6: Regression results for Model 1 and 2

Dependent Variable	***Model 1 - Total delay minutes***	**Model 2 - Delay attributed to weather**
Explanatory variable	**Coefficient**	**Coefficient**
Mean temperature	-80.7106	-179.572*
Temperature difference	997.0682*	414.5008**
Rainfall	29.46919***	32.28229***
Snow	970.3738***	116.3636
Windspeed	759.6765***	548.4503***
Period dummy 7	5939.345*	1762.618**
Period dummy 8	20226.1***	4384.456***
Period dummy 9	27481.24***	5709.893***
Period dummy 10	6644.655***	625.8859**
Period dummy 11	6967.211***	103.3842
Period dummy 12	7451.556***	3166.713***
Time	157.1587***	3.418186
Constant	-25962.98*	-10382.6***
Observations	2,457	2,457
Within R squared	0.2646	0.2260
Between R squared	0.8742	0.8277
Overall R squared	0.7598	0.3476

*** Indicates significance at the 1% level, ** indicates significance at the 5% level and * indicates significance at the 10% level.

Model 1 has an overall r-squared of 0.7598 which means that my model explains 75.98% of the overall variation in delay minutes. This model has a between r-squared value of 0.8742, meaning 87.42% of the variation between train operators is accounted for and a within r-squared of 0.2646, which means only 26.46% of the variation in delay minutes within each train operator is explained.

For a weather condition to be shown to have a real-life effect on delay minutes, the result needs to be statistically significant. When a result is significant at the 5% level, this means the there is only a 5% chance the relationship is due to chance. Model 1 results show that all the variables of interest in my literature review are significant in 25 causing delay. Temperature difference is significant at the 10% level, meaning higher variation in temperature in a month leads to more delays. A 1 degree increase in the difference between the hottest and coldest average temperature will increase delay by 977 minutes. Rainfall, snow and windspeed are all significant at the 1% level. A 1mm increase in rainfall will increase delay by 29 minutes. An additional day in which 50% of the ground is covered with snow will increase delay by 970 minutes. An additional knot of windspeed, will lead to an additional delay of 760 minutes. Model 1 also shows that periodic dummies, and the month they are associated with, have an effect on delay. I have only reported the results for dummies 7 to 12, which represent weather for the months of September to February to show the effect of autumn and cold weather months on delay. Period 8 (October) and Period 9 (November) are significant at the 1% level, showing that the presence of leaves on the track cause delay.

To assess the validity of Model 1, I ran the same model specification with a dependent variable of delay minutes which had been directly recorded as due to weather events, the results are reported for Model 2 in the table above. The Hausman test again indicated that a random effects model could be used. This model had evidence of heteroskedasticity, but first-order autocorrelation was not present. I used robust standard errors to adjust the standard errors for heteroskedasticity to allow inferences to be made from the results. Model 2 has a lower overall r-squared meaning these variables explain less of the variation in delay attributed to weather than they do for total delay minutes. In Model 2, average temperature is significant at the 10% level. A warmer mean temperature reduces delay minutes. Snow is no longer significant in causing delay, but this could be explained by the likelihood that trains would have been cancelled if there were large amounts of snowfall, meaning delay minutes would not be recorded for this under the extreme weather category.

4.2 The impact of extreme weather on delay attributed to weather

I then assessed the impact extreme weather conditions had on delay. I included high and low temperature, rain and wind as defined in the methodology section of this paper. The Hausman test indicated that a random effects model should be used and due to the presence of autocorrelation and heteroskedasticity, I used robust standard errors in this model.

Equation 2 shows the equation used to model the relationship

$$\begin{aligned} DM = {} & \beta_1 MT + \beta_2 TD + \beta_3 HT + \beta_4 LT + \beta_5 R + \beta_6 HR + \beta_7 LR + \beta_8 S + \beta_9 W + \beta_{10} HW \\ & + \beta_{11} LW + \beta_{12} PD1 + \beta_{13} PD2 + \beta_{14} PD3 + \beta_{15} PD4 + \beta_{16} PD5 + \beta_{17} PD6 \\ & + \beta_{18} PD7 + \beta_{19} PD8 + \beta_{20} PD9 + \beta_{21} PD10 + \beta_{22} PD11 + \beta_{23} PD12 + \beta_{24} T \\ & + \beta_{25} PK + \beta_{26} PJ + \beta_{27} MS + \alpha + (\mu + \epsilon) \end{aligned}$$

Where HT is high temperature, LT is low temperature, HR is high rain, LR is low rain, HW is high wind and LW is low wind.

The results from the most relevant variables in this regression are outlined in Table 7 using a random effect generalised least squares model, with robust standard errors.

Model 3 has similar r-squared values to model 1. This means the results explain the same amount of variation within and between train operators as model 1.

Under this model, temperature difference is no longer statistically significant, meaning it cannot be concluded that it affects delay minutes. When the temperature is above 21 degrees, delay is increased by 4,694 minutes. This result is significant at the 1% level. Temperature below 0 is significant at the 5% level and causes delay increase by to be 3,666 minutes. Rainfall in this model is still significant but at the 10% level and has a similar causal relationship to delay as in model 1. Low rainfall is significant at the 1% level, meaning when rainfall in a month rainfall is below 23mm, delay minutes increase by 4,810 minutes. Snow remains significant at the 1% level but increases delay by a smaller amount than in model 1. Windspeed itself is no longer significant but high and low windspeed is significant at the 1% and 5% respectively. Windspeed above 12 knots lead to longer delays and windspeed below 6 knots reduces delay time. Periods 7 and 8 remain significant in causing delay by a similar amount as the results in model 1.

Table 7: Regression results for model 3 and 4

Dependent variable	Model 3 - Total delay minutes	Model 4 - Delay attributed to weather
Explanatory variable	**Coefficient**	**Coefficient**
Mean temperature	*-329.629*	*-323.3073****
Temperature difference	*479.4391*	*153.3196*
High temperature	*4694.087****	*1229.163****
Low temperature	*3665.954***	*1209.974*
Rainfall	*27.26253**	*25.23796****
High rainfall	*967.4066*	*2023.915***
Low rainfall	*4810.396****	*1686.574****
Snow	*685.8273****	*14.4028*
Windspeed	*212.1029*	*262.507****
High wind	*7262.36****	*4709.92****
Low wind	*-5728.98***	*389.9061*
Period dummy 7	*7632.492***	*2461.98****
Period dummy 8	*20553.19****	*4719.394****
Period dummy 9	*26499.77****	*5318.24****
Period dummy 10	*3820.755**	*-1074.395****
Period dummy 11	*5536.238****	*-739.8768***
Period dummy 12	*5029.695****	*1791.427****
Time	*158.5649****	*5.956646**
Constant	*-14403.4*	*-4410.771****
Observations	*2,457*	*2,457*
Within R squared	*0.2721*	*0.2595*
Between R squared	*0.8735*	*0.8099*
Overall R squared	*0.7600*	*0.3707*

*** Indicates significance at the 1% level, ** indicates significance at the 5% level and * indicates significance at the 10% level.

Model 4 results report the effect of extreme weather on delay minutes which are directly attributed to weather. Again, this is a random effects model with robust standard errors. In this model, mean temperature is now significant at the 1% level in causing delay and snow is no longer significant. Low windspeed is shown to increase delay however this result is not statistically significant so it cannot be concluded that this result is not due to chance. This model has lower r-squared values but supports the results in Model 1, as the same kind of relationship is shown between most variables of interest and delay minutes.

4.3 The impact of weather on cancelled trains

I also explored how the variables used to model delay minutes impacted the number of trains cancelled. The Hausman test gave a test statistic of 1, meaning the appropriate model to use is random effects. I also tested for heteroskedasticity and autocorrelation. There was evidence of heteroskedasticity and autocorrelation at the 1% level, so I used robust standard errors to give consistent estimations.

Table 8: Regression results for Model 5

Number of trains cancelled	
Explanatory variable	**Coefficient**
Average temperature	0.255219
Temperature difference	-4.16233
Low temperature	269.0923***
High temperature	203.0811*
Rainfall	0.272853
High rain	16.09288
Low rain	-31.4661
Snow	9.007957
Windspeed	-8.72195
High wind	209.6844*
Low wind	70.725
Period_dummy7	-87.3727
Period_dummy8	38.54047
Period_dummy9	92.16886***
Period_dummy10	37.59331
Period_dummy11	-79.5644
Period_dummy12	40.54165
Time	6.835271
Constant	-306.937
Observations	1,638
Within R squared	0.1442
Between R squared	0.8036
Overall R squared	0.6410

*** Indicates significance at the 1% level, ** indicates significance at the 5% level and * indicates significance at the 10% level.

Model 5 has an overall r-squared value of 0.6410, meaning 64.1% of overall variation in delay minutes is explained by the model. This model shows a less significant relationship between the variables of interest and performance than Models 1 to 4. Most variables do not have a significant impact on the number of trains which are cancelled. This means that I can only conclude that there is a causal effect that is not due to chance for the following variables. Low temperature is significant at the 1% level and increases the number of trains cancelled by 269 trains. High temperature is significant at the 10% level and increases the number of cancelled trains by 203 trains. High windspeed is also significant at the 10% level. This increases the number of cancelled trains by 209. Period 9, which represents November, is significant at the 1% level, and therefore adds to the validity that Autumn months worsen performance.

5. Discussion/Conclusion

5.1. Summary of main results

This study aimed to explore the impact weather has on train operator performance within the UK. Studies using data from England, Wales and Scotland have not yet been explored in this context. I aimed to assess how weather conditions, which have been shown to be relevant to other countries, affect the train operators in England, Wales and Scotland. I assessed two key aspects of performance, assessing separately the effect of weather on delay minutes and number of trains cancelled. According to previous literature, delay is caused by snow, high rain and very dry weather, wind, cold temperatures and extremely hot temperatures. Seasonal effects have also been shown by the significant impact of the month of November on performance.

I was able to show that key weather conditions discussed in my literature review affect delay minutes in the UK. I have shown that hot and dry weather conditions have the greatest effect on delay minutes. I have also shown that heavy rain, hot temperatures and high windspeed lead to increased delay. The evidence supports my hypothesis that inclement weather causes delay, and I have been able to conclude that an increase in certain weather conditions will increase delay minutes. The results I have obtained for total delay minutes do not provide any unexpected results. However, when I modelled just delay attributed to extreme weather, some results were less intuitive. For example, snow was not found to have a significant effect on delay minutes, however when looking at all delay minutes, snow is shown to increase delay and this result is statistically significant.

Cancellations and weather show a less defined relationship and variables which I would expect to be significant in causing cancellations were not. Snow and rainfall had no significant effect on cancelled trains in my analysis. This is unexpected since intuition would suggest that snow and flooding due to high rainfall should have an impact in the number of trains cancelled. Model 5 does however use a smaller dataset than delay minutes and so this smaller sample may be yielding less robust results. This model does support the delay model in that extreme temperatures, high windspeed and the month of November have significant effects on delay.

5.2. Policy implications

Network Rail, who own the majority of the railway infrastructure in the UK, released their Third Adaptation report in December 2021, which outlines their plans for dealing with the impact of climate change (Network Rail, 2021). In this report Network Rail say then plan to adjust their approach to asset management so that infrastructure can cope with future weather conditions. Their effort seems to be focused on reducing the impact of flooding by increasing drainage, stabilising slope to reduce landslides and enhancing maintenance to withstand high temperatures (Network Rail, 2021).

The key policy implications from my analysis are that the greatest effect on delay minutes come from high temperatures and low rain. The UK does not regularly experience high temperatures, but the impact of a warming climate makes this type of weather and the risk it poses likely to be more frequent. The largest impact on delay minutes, from my analysis, comes due to seasonal effects, especially for the month of November, therefore efforts should also be prioritised to protect against this.

5.3 Recommendations for future research

These models do not capture the relationship between performance and weather as accurately as data which is disaggregated daily would. Repeating this study with daily observations would be preferable and allow for the exact weather conditions and delay or cancellations caused to be examined. When working with periodic data, it is not possible to assess what the exact daily temperature or rainfall, for example, was and how this relates to train operator performance on that day. This however was not possible for my study as daily delay and cancellation data is not published.

It would be preferable to extend this research to include variables for track specific characteristics which are not captured currently in my dataset. Train operators run on different parts of the railway network. Different areas of track have a different mix of electrification, which would be more disrupted by heavy rain or snow due to issues with signals being interrupted or electrical wiring damaged by high wind, which in turn could worsen a train operator's performance. Track is also more susceptible to flooding due to high rainfall in some areas, which again would lead to more delay and cancelled trains during a period of heavy rain. Controlling for specific track characteristics would improve the robustness of my analysis, since issues with railway track have a direct effect on whether train operators can run their services or not.

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Annex 1: Correlation coefficients

Table 9: Total delay minutes

	Delay Mins	Mean Temp	Temp Difference	Low Temp	High Temp	Rainfall	High Rain	Low Rain	Snow	Wind speed	High wind	Low wind	Passenger km	Passenger journeys	Managed stations	Time
Delay Mins	1															
Mean Temp	-0.034	1														
Temp difference	-0.130	0.673	1													
Low Temp	-0.021	-0.27	-0.032	1												
High Temp	0.028	0.442	0.374	-0.048	1											
Rainfall	0.108	-0.202	-0.486	-0.007	-0.180	1										
High Rain	0.079	-0.128	-0.206	0.046	-0.062	0.606	1									
Low Rain	-0.044	0.122	0.274	0.004	0.066	-0.339	-0.052	1								
Snow	-0.008	-0.553	-0.420	0.293	-0.112	0.065	0.019	-0.061	1							
Windspeed	0.029	-0.489	-0.375	0.112	-0.243	0.325	0.214	-0.224	0.209	1						
High Wind	0.027	-0.220	-0.167	0.099	-0.063	0.262	0.166	-0.053	0.106	0.624	1					
Low Wind	-0.023	0.133	0.106	-0.023	-0.036	-0.191	-0.030	0.553	-0.055	-0.264	-0.031	1				
Passenger km	0.665	0.030	-0.031	-0.055	0.035	-0.014	-0.005	-0.012	-0.021	-0.004	-0.005	0.000	1			
Passenger Journeys	0.690	0.059	0.110	-0.006	0.059	-0.067	-0.021	0.021	-0.078	-0.003	-0.002	0.002	0.653	1		
Managed Stations	0.679	-0.053	-0.134	-0.001	-0.041	0.209	0.189	-0.036	0.041	-0.001	0.000	0.001	0.267	0.494	1	
Time	0.140	0.087	0.075	-0.047	0.120	-0.009	-0.029	-0.057	-0.148	-0.092	-0.103	-0.037	0.063	0.043	-0.002	**1**

Table 10: Number of trains cancelled

	Trains cancelled	Mean Temp	Temp Difference	Low Temp	High Temp	Rainfall	High Rain	Low Rain	Snow	Wind speed	High wind	Low wind	Passenger km	Passenger journeys	Managed stations	Time
Trains cancelled	**1**															
Mean Temp	0.003	**1**														
Temp difference	-0.016	0.680	**1**													
Low Temp	0.044	-0.254	-0.041	**1**												
High Temp	0.073	0.466	0.382	-0.047	**1**											
Rainfall	0.039	-0.196	-0.519	-0.050	-0.197	**1**										
High Rain	0.039	-0.099	-0.225	0.024	-0.062	0.595	**1**									
Low Rain	-0.026	0.167	0.291	0.031	0.102	-0.363	-0.051	**1**								
Snow	-0.020	-0.567	-0.413	0.242	-0.127	0.150	0.047	-0.101	**1**							
Windspeed	0.028	-0.527	-0.416	0.117	-0.234	0.349	0.208	-0.276	0.321	**1**						
High Wind	0.028	-0.178	-0.144	0.069	-0.058	0.226	0.160	-0.048	0.175	0.593	**1**					
Low Wind	-0.041	0.159	0.124	-0.026	-0.047	-0.236	-0.035	0.642	-0.071	-0.322	-0.032	**1**				
Passenger km	0.535	0.028	-0.039	-0.039	0.034	-0.014	-0.009	-0.002	-0.015	0.001	-0.003	-0.007	**1**			
Passenger Journeys	0.771	0.059	0.114	0.019	0.056	-0.070	-0.035	0.029	-0.086	0.001	-0.001	-0.002	0.636	**1**		
Managed Stations	0.517	-0.054	-0.136	0.008	-0.046	0.215	0.195	-0.030	0.048	-0.001	0.000	0.001	0.254	0.488	**1**	
Time	0.153	0.084	0.053	-0.023	0.112	0.063	0.010	-0.138	-0.131	-0.032	-0.093	-0.209	0.022	0.006	-0.004	**1**